The reaction of BRICS stock markets to COVID risk

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Table of Contents

List of Abbreviations

Abbreviation	Meaning
ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller Test
AIC	Akaike Information Criteria
AR	Autoregressive
ARMA	Autoregressive moving average
BIC	Schwarz–Bayesian information criterion
BRICS	Brazil, Russia, India, China, South Africa
CAPM	Capital Asset Pricing Model
CBR	Central Bank of Russia
CEAP	Coronavirus Emergency Aid Packages
COVID-19	Coronavirus disease 2019
EMT	Efficient Market Theory
EPU	Economic Policy Uncertainty
EU	European Union
EVD	Ebola Virus Disease
FDI	Foreign Direct Investments
FTSE	Financial Times Stock Exchange
GARCH	Generalized Autoregressive Conditional Heteroscedastic
GDP	Gross Domestic Product
GRI	Government Response Index
IBrX	Índice Brasil (Index for Brazil)
IFC	International Finance Corporation
IHR	International Health Regulations
IMF	International Monetary Fund
JSE	Johannesburg Stock Exchange
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
LM	Lagrange Multiplier
MA	Moving average
MERS	Middle East respiratory syndrome

MOEX	Moscow Exchange
MSCI	Morgan Stanley Capital International
NIFTY 500	National Stock Exchange Fifty 500
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
OxCGRT	Oxford Covid-19 Government Response Tracker
PACF	Partial Autocorrelation Function
RBI	Royal Bank of India
SARS	Severe Acute Respiratory Syndrome
SARS-CoV-2	Severe Acute Respiratory Syndrome Coronavirus 2
SME	Small and Medium Enterprises
SZSE	Shenzhen Stock Exchange
UNCTAD	United Nations Conference on Trade and Development
US / USA	United States / United States of America
VIX	Volatility Index
WHO	World Health Organization

List of Figures

List of Tables

List of Equations

1. Introduction

In the early 1970's the overall perception of the world's economies was split into markets of developed countries and those of the less developed. The term "emerging market" was first used by the International Finance Corporation (IFC) of the World Bank grouping the stock market indices of those countries, which they started to calculate (Bruner, 2003, p.1). Despite various interpretations and the global understanding of an emerging market as a market in a transition to higher level of economic development, the definition of such economies remained indistinct. According to Standard & Poor's emerging markets must fulfill two criteria, firstly "it is a low-, low-middle, upper-middle income economy as defined by the World Bank" and secondly "its investable market capitalization is low relative to its most recent Gross Domestic Product (GDP) figures" (Bruner, 2003, p.17). Since the early 1990s, the position of emerging markets in global economy was growing stronger, driven by world globalization in the form of increased cross-border trade, the commodities super cycle, and the rise of global supply chains. In the last 20 years the share of emerging markets in global stock market capitalization has gained traction and managed to increase significantly from 3% to 14%. At the same time GDP was increasing from 24% and today reached 43% of the world GDP. (Credit Suisse, 2021).

Over time, few markets stood out to be the most significant in terms of their input to economic development and foreign trade. These countries were Brazil, Russia, India, China. Later, also South Africa became part of the group commonly named BRICS. As a result of such rapid-growth, emerging markets were offering a greater rate of return and therefore became integral part of various investment portfolios (Wheatley, 2019). But the growth path of emerging markets also used to be highly volatile, which is also explained by their reaction to historic events, such as wars, political unrest, and crises. Understanding investor behavior in the light of the historic experience of a high risk therefore captured the attention of academics and researchers around the world. In different studies, their interest was not only to investigate the role of emerging markets in a diversified portfolio but also its associated volatility risks.

Historic events have shown, that during times of turmoil, whether if it is a political or a health threat like the recent pandemic spread of the Corona Virus Disease 2019 (COVID-19), the level of economic uncertainty usually goes up, involving negative effects like higher inflation rates, unemployment, devaluation of the currency, lower economic growth, and turbulence at stock markets. Nevertheless, stock prices can be also affected by various other interrelated or non-economic and/or political rates such as government response to the specific event. That was already proved by researchers during other disease outbreaks such as “Severe Acute Respiratory Syndrome” (SARS) (Loh, 2006) and “Ebola Virus Disease” (EVD) (Ichev & Marinc, 2017).

Despite the growing knowledge about significant events, uncertainty, and governmental response, forecasting financial market behavior has remained a major challenge for researchers, investors, and speculators. Assuming, that the future values at least partially contain information of past data, events and the present, financial time series have essentially proven to be none-stationary and noisy. Such suggestions led to a lot of debate among economists about the efficient market hypothesis. Still, many studies show evidence, that there is a trend in a sustained increase or decrease in price over a substantial period (Abu-Mostafa & Atiya, 1996). Resultantly, investors and portfolio managers collaborate with researchers attempting to improve forecasting models to make profit from market inefficiency (Farid, Tashfeen, Mohsan, Burhan, 2021, p.1).

The most recent event of turmoil with a global impact - the COVID-19 outbreak - provides a unique research opportunity to investigate, if the market volatility, brought by the pandemic, is inseparable linked with low equity returns. Therefore, the main interest of this thesis is to determine the effect of the COVID-19 outbreak on the stock markets of BRICS economies. The rationale is based on the idea, that the uncertainty about the future leads to high systematic volatility in the economy and future cash flows become very risky. Therefore, and secondly, this thesis also analyses how the Economic Policy Uncertainty (EPU) moves along with stock returns. Finally, the consequence of government intervention and its relationship with stock markets will be investigated. The study will therefore include comparative analysis of economies, indicators for COVID cases, reaction of stock markets and government responses to the outbreak.

2. Initial Position and Posing of the Problem

In 2001, Nassim Nicholas Taleb refers in his "black swan theory" to unexpected events of large magnitude and consequence and their dominant role in history (Taleb 2007). With the sudden pandemic spread of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) - commonly called coronavirus, the world and the global economy was experiencing such "Black Swan" event with a magnitude and impact, that would provide researchers and academics a new opportunity to test their theories.

A truly exogenous and disruptive event has unprecedented nature, which makes it a unique and ideal environment to study investor reactions. Ramelli and Wagner (2020, p.1-2) state that there are three specific characteristics that differ the COVID-19 health crisis from different global crises that have happened within the last century. Firstly, other significant events have at least been partially endogenous to corporate decisions. Secondly, this health crisis can be considered an outlier event, which hasn't been discussed in advance and had a low probability of occurring. Finally, past events were relatively slow to unfold. With these three differing characteristics, the COVID-19 health crisis offers the opportunity to gain valuable insights about market behavior in such a unique environment.

At present, volatility is considered the most important metric to measure financial risk changes. The early origins of volatility's use can be found in financial practices of Markowitz and Sharpe. Harry Markowitz developed a modern portfolio theory, which implied a direct link between an asset's expected return and its risk (Markowitz, 1952). In this theory, risk is equivalent to the volatility and in this term refers to the degree of uncertainty related to magnitude of the security's value variation. In the heart of this theory lie several fundamental assumptions: the investor is risk averse and rational (they seek to minimize risk and maximize the return), the market is efficient, and information is immediately absorbed in the market (Mangram, 2013, p.1645). The capital asset pricing model (CAPM) pioneered by William Sharpe and John Lintner in early 1960s was based on Markowitz's portfolio model. It considered an asset's sensitivity to systematic risk and the expected returns of both, the market, and a risk-free asset (Volkart & Wagner, 2018, p.225, 229). In principle, the model predicts, that the relation between an asset's sensitivity, beta, and return is linearly positive. Some initial empirical tests of CAPM model have found though, that the risk-to-return relation is flatter than the model predicts. The finding was confirmed by various subsequent studies, which even found the anomalous (in this term negative) relation between risk and return as the volatility effect (Blitz, Falkenstein, Vliet, 2014). Furthermore, Blitz and Vliet (2007), Frazzini and Pederson (2014), Baker and Haugen (2012) and some other academics found the existence of anomaly in international developed and emerging equity markets.

Late 2019, COVID-19 started spreading within China and soon also beyond its borders. News about exponentially increasing new cases of active infections and high mortality rates caused significant global concerns about public security and health. Both measures, new cases, and mortality rates, were visible across all media in high frequency and became significant for the definition of a countries pandemic risk level. Through declining supply, decrease in consumer spending, the closing or restriction of economic activities and sharp rise of oil prices the world immediately felt the impact of the pandemic (Narayan, Phan & Liu, 2020). With changing number of new cases and mortality rates, governments would react and impose new restrictions or ease regulations, of which both caused frequent change of public behavior and economic effects. The impact was not only weakening for the economies, but it also caused a high level of uncertainty, including the uncertainty about the timeframe of the event and possible outcome scenarios based on highly differing theories about the development of the crisis. Such uncertainty did not only raise the concern of the public, but also of investors. As a result, the increasing volatility triggered investors to sell their shares, to reduce investments or postpone their investment decisions. Considering the theory of the relationship between uncertainty and volatility, this change in investors' behavior as a reaction to it had an impact to the global financial markets (Norrestad, 2021).

While the COVID-19 health crisis led to a global economic recession, the BRICS countries showed a significant divergence in terms of intensity and duration of the pandemic. Notably, that among the BRICS countries India, Brazil and Russia were the countries with the highest cases of infections worldwide. Apart from China, all the countries also showed a contraction in economic growth in 2020. The related stock market crash during the time of the pandemic spread, therefore provides valuable real-life data, especially with the focus on BRICS countries, that can be used to study the relation between the risk during such a rare event like the COVID-19 pandemic and stock market performance.

Unlike other events, the challenge of a global pandemic crisis in combination with limited options to manage such complex event did not only increase volatility, but also put stronger focus on political decisions, international comparison of strategies and efficiency of governmental responses. Prompt fiscal and monetary support indicated economic stabilization already in the second quarter of 2020. Broad investments accelerated the growth of certain industries and the introduction of vaccination programs, which were rolled-out in the second half of 2020, reinforced economic recovery and provided signs for even stronger recovery in 2021. Active government interventions significantly influenced the prevention of worst-case economic impact of the COVID-19 pandemic (RBI, 2021). Considering the magnitude and significance of the government responses during the COVID-19 crisis, corresponding data can therefore be used to analyze the relation of government response to the stock market developments and individual industry segments at times of high uncertainty.

3. Goals and Objective

To extend the limited availability of research about the performance of BRICS stock markets during the COVID-19 pandemic, this paper aims to conduct a comparative study of the market reaction in each BRICS country to the economic and health crisis, caused by the pandemic outbreak. Therefore, each countries' market will be represented by the most significant index for that country: IBrX 100 Index for Brazil, MOEX Index for Russia, NIFTY 500 Index for India, Shenzhen Component Index for China, FTSE/JSE Africa all share Index

As a fundamental part of the study the development of these stock markets will be analyzed over a period of 24 months, from Jan 1st, 2020, to Dec 31st, 2021. The main goal will be to investigate the impact of COVID-19 on the stock market value and to examine the relationship and predictable power of new reported COVID-19-cases, new mortality cases as well as economic policy uncertainty index and government response index. While government reactions might have caused significant disruption to some industries, it is expected, that other industries could benefit and grow as a result. In case one countries' market will show a significant impact based on the regression results, the research will be further extended. An additional cross-industry analysis will be conducted for the one chosen country to also investigate the impact of COVID-19 outbreak on individual industries within that country.

It is with these considerations, that the null and alternative hypothesis are defined as:

H_1: The number of new reported COVID-19 cases doesn't have a significant predictable power on the stock market.
H_a: The number of new reported COVID-19 cases has predictable power on the stock market.

H_2: The number of new mortality cases doesn't have predictable power on the stock market.
H_a: The number of new mortality cases has predictable power on the stock market.

H_3: Economic policy uncertainty doesn't have a significant impact on the stock market.
H_a: Economic policy uncertainty has a significant impact on the stock market.

H_4: Government response doesn't have a predictable power on the stock market.
H_a: Government response has a predictable power on the stock market.

Since financial time series usually include floating component and time varying volatility, it was decided to use daily time series in combination with the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model with Autoregressive Moving Average (ARMA) for the mean component. This method will allow to test the predictable power of the variables in question adding them both in mean and volatility equation.

To provide a clear structure, this paper is divided into different chapters, each of them covering specific steps of the research process. Chapter 4 is providing an overview of the Status-Quo. It outlines existing literature, which was used to study the impact of the COVID-19 outbreak on economies, both worldwide and the observed countries. At the same time, the chapter facilitates the methodology for analyzing financial time series. In summary it presents the current state of research and identifies research gaps. The applicable theory about the pandemic outbreak and its impact on economies, is explained in Chapter 5. It provides a review of general timelines and answers questions about global stock market reaction, risk impact across BRICS economies, the influence of economic policy uncertainty and policy response on stock market returns. The data used for the analysis is explained in Chapter 6, both for depended and independent variables. The descriptive statistics will close the chapter and lead to the details of methodology and research design in Chapter 7. Every step of the data analysis is explained and both, the presented estimation results and the methodology are verified through various tests for data appropriateness and model adequacy. The overall interpretation of the data, if and how BRICS markets were impacted by the COVID-19 spread and the related volatility, uncertainty and government response is summarized in Chapter 8 as the result of the study. As extension, Chapter 9 provides a deep dive into the cross-industry analysis for one selected country, where the study was showing some significance in impact. The same methodology will be employed for industry segments for more detailed results and interpretation. In chapter 10 the findings from the previous chapters are generalized and systematized, the limitations and implementations are specified. In the discussion, which is followed in the same chapter, the findings and approaches of current research will be compared with other researchers.

4. State of Research and Research Gaps

In the last several decades, when the most significant economic crises took place, scholars and academics have taken a growing interest in the investigating the impact of economic crisis on stock markets. Consequently, the field has seen a rise in empirical studies since the outbreak of COVID-19. To provide an overview of existing information, this section reviews relevant theoretical and empirical studies related to effects of crises on economies, especially the health crises caused by the COVID-19 spread.

In different events, academics and economists put high efforts into studies of financial and political crisis and their relation to recessions, explaining growth and fluctuations (Cerra & Saxena, 2008). Reinhart and Rogoff (2009) performed a comparative historical analysis, which confirmed the findings, that severe financial crises show strong effects on asset prices, output, and employment. The Asian financial crisis, called "Asian contagion", was caused by the collapse of Thailand's currency baht in 1997, followed by the devaluation of many other Asian currencies, which finally led to a recession in Asian economies (Radelet & Sachs, 1998). Allen and Carletti (2010) investigated the root cause of the global financial crisis in 2008. A loose monetary policy in combination with subprime mortgages, weak regulatory structure and a high leverage in the banking sector were defined as the main reasons for the financial crisis, which led to transition into recession.

Existing literature was indicating, how financial and political crises could relate to economic decline. But pre-COVID only few economic crises in recent history were related to health crises. Therefore, the number of literatures investigating the impact of a health crisis on economy was comparably small. Ma, Rogers, and Zhou (2020) examined the immediate effect of six modern health crises: 1968 Flu, SARS (2003), H1N1 (2009), MERS (2012), Ebola (2014), and Zika (2016) and laid a foundation in understanding the economic impact of previous pandemics. Their results showed first evidence, that a typical health crisis lowers the GDP by approximately three percent. While the effects are visible for at least five years, fiscal policy has proven to mitigate them. More research was devoted to exam the effect of the previous SARS virus disease, which affected 26 countries. Evidence of a negative impact of the spread of the SARS virus on stock markets was found in Canada, China, Hong Kong, Singapore, and Thailand (Loh, 2006). Also researches around Ebola outbreak events throughout 2014-2016 have revealed that US companies with exposure of their operations in West African countries were experiencing negative return and increasing volatility because of those events. Those Ebola related events effected investors' perceived risk (Ichev & Marinc, 2017).

Early studies have therefore shown evidence even before COVID-19, that health related crises impact volatility, investors behavior and economic performance. But since the outbreak of COVID-19, as a phenomenon with a significant magnitude and influence, the number of studies and literature began to increase rapidly focusing on the impact on economics and the corresponding policies' responses to it. Furthermore, as the pandemic is still in process in some countries and the aftermath continues to emerge, it remains to be of high interest to academics, market participants and policy makers. As such, the United Nations Conference on Trade and Development (UNCTAD, 2020) has analyzed and compared two crises, the global financial crises in 2008 and the COVID-19 crisis and pointed-out three channels, which could cause the most damage to economies: demand, supply, and finance. In addition, the research offers mechanism of measures that must be done to avert global depression.

The effects of the pandemic on economies within developed and emerging countries are the area of a study, which received a lot of attention. Bakry et al. (2021) have found a positive and significant relation between COVID-19 confirmed cases and volatility in both markets with differing conditions by the contexts of the markets. Also, the research revealed a difference in relation between volatility and stringency of government actions, which was positive in emerging markets and negative in developed markets. The similar conclusions were made in the study of Senol and Zeren (2020). The authors investigated the global stock market development during the period of the first four months of the pandemic, represented by key indices from Morgan Stanley Capital International (MSCI): MSCI World, MSCI Emerging markets, MSCI Europa and MSCI G7. The applied Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test showed a negative long-term relation between the stock market returns and COVID-19 cases and mortality rates. Further contribution to the understanding about the changing impact of the pandemic over time was made by Topcu and Gulal (2020). The data revealed that negative impact of pandemic on 26 emerging stock markets was at the highest magnitude in March 2020, then started gradually to fall and contracted by mid of April. Moreover, the paper also presented Asian emerging markets as the area with the biggest impact, the smallest impact was monitored in countries, where government response measures were announced in time and larger stimulus packages were introduced. Analyzing the stock market indices of G7 countries over first five month of the COVID-19 outbreak by applying the GARCH model, Yousef (2020) found evidence for the significant positive impact of daily new cases and the growth rate of daily new cases on the standard deviation of index returns.

Finally, coming close to the reaction of BRICS countries, which is the core object of this study. Scherf et al. (2022) analyzed the reaction of OECD[1] and BRICS markets on the COVID-19 pandemic and found an important insight: In the period from January 22nd to May 20th, 2020, neither local nor global new COVID-19 cases had any significant impact on local stock markets. Moreover, in the period from January 22nd to March 27th, 2020, the increase of global cases has a significant positive effect on stock markets. However, the analysis also revealed, that the introduction of the first strict measures as government response had negative effects on the respective stock markets. The authors explain the reaction with negative economic consequences, which stock markets would expect from government restrictions. In contrary, the results of another economic publication applying an event study method revealed the opposite: A negative effect of COVID-19 across all the G7 and BRICS markets except for China. The insignificant impact on Chinese Benchmark Index indicates substantial governmental steps in containing the virus (Ledwani et al., 2021). Different findings were published in another paper, where daily growths in total confirmed infection cases and cases of death showed a significant negative relation with Chinese stock Hang Seng index and Shanghai Stock Exchange Composite Index (Al-Awadhi et al., 2020).

Using a wavelet coherence analysis, the paper of Asofo-Adjei et al. (2020) differs from other studies about the impact of COVID-19 cases on financial market by analyzing the co-movements of economic policy uncertainty and stock returns. It depicts a weak co-movement between global EPU and stock markets in Africa in a short term (up to 16

[1] The Organization for economic Co-Operation and Development, the members of which are 38 countries

days), but results show stronger co-movements in a long-term perspective (Asofo-Adjei et al., 2020).

There is already existing literature about the reaction of stock markets to the COVID-19 pandemic. Despite the similarities of some topics on a high level, each study was based on different methods and varying timelines. Time-series analysis models, event study methods, causality tests and others can reveal different results based on different focus or perspective. At the same time, results could change once factors like government response or uncertainty were included as influencing variables. Still, each result provides valuable information exactly because of each specific perspective. Therefore, this general field of study remains valuable and offers opportunity to further explore. Hence, this study will not only analyze the effect of COVID-19 on BRICS markets, but economic policy uncertainty and government response are added as dimensions to the examination. This new approach, using the ARMA-GARCH model with different variables, adds a new perspective and will provide additional input and ideas for the overall understanding of market reactions as well as for further COVID-19 related studies as some countries are still today managing the spread of the virus or its consequences.

5. Applicable Theory

5.1. Timeline of COVID-19 spread in BRICS countries

The first official COVID-19 cases were detected in Wuhan City, China and were reported by China Country Office of the World Health Organization (WHO) on December 31, 2019. Despite China's early introduction of quarantines and travel restrictions, the SARS-CoV-2 virus and its related disease was spreading around the globe with unrelenting speed. Within few weeks cases appeared in more than 200 countries and once it crossed a border, it continued its spread uncontrollably across all levels of a country's society. On March 11th, 2020, when 4'292 COVID-19 related cases of death were reported and the number of active COVID-19 infection cases exceeded 118'000, the WHO declared the situation as a global pandemic. The rapid growth of new infection cases with high hospitalization rates in combination with limited resources for isolation and intensive care, lack of treatment options and high mortality rates as a result, soon became a threat to healthcare infrastructure and public life in many countries. By the end of March 2020 governments in well over 100 countries were forced to introduce strict measures including partial or full lockdown (BBC, 2020a). Restricting social life to the level in which people were asked to stay at home and avoid any type of social contact outside the own household, was the final approach to break infection chains and prevent a collapse of the healthcare system. While essential businesses, e.g., for food supply etc. could continue to operate under difficult restrictions, others had to find new ways to organize their businesses or had to close their business entirely. The lack of clarity and experience how to deal with such situation caused high levels of uncertainty in those countries' population and wreaked a havoc on stock exchanges and financial sectors across the globe. Especially dramatic was the period between March 6th and March 18th, when several global stock markets plummeted more than 20% of their value, bringing a collective hysteria and panic (Statista, 2020).

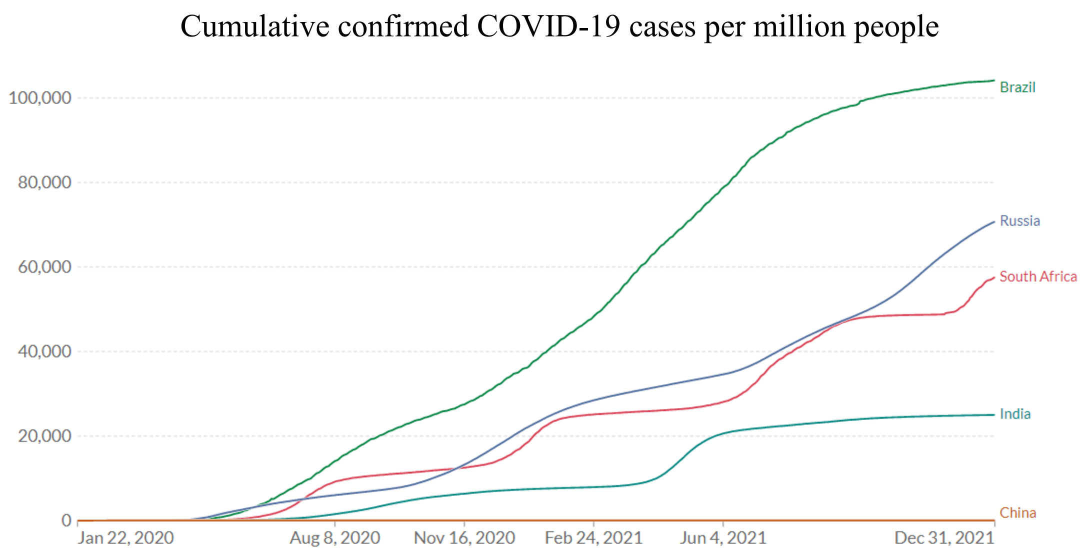


Figure 1: Line Chart of Cumulative confirmed COVID-19 cases per million people during the period 01.01.20-31.12.21 (Source: ourworldindata.org)

Despite the fast spread of the virus, the historic timeline of the COVID-19 spread differs for each country. At first, each country was experiencing different start dates influenced by the time required for the virus to appear in one country. Figure 1 shows the cumulative history of confirmed cases as a ratio of the total population for BRICS countries to compare the relative situation in one country. Each country shows varying developments in different waves, influenced by different variables, seasonality, mutation type of the virus, government response as well as vaccination programs. While the initial phase of the global pandemic caused the most uncertainty, in a retro perspective, the cumulative infection numbers in spring 2020 become invisible in Figure 1 in the face of the magnitude the virus would spread over time.

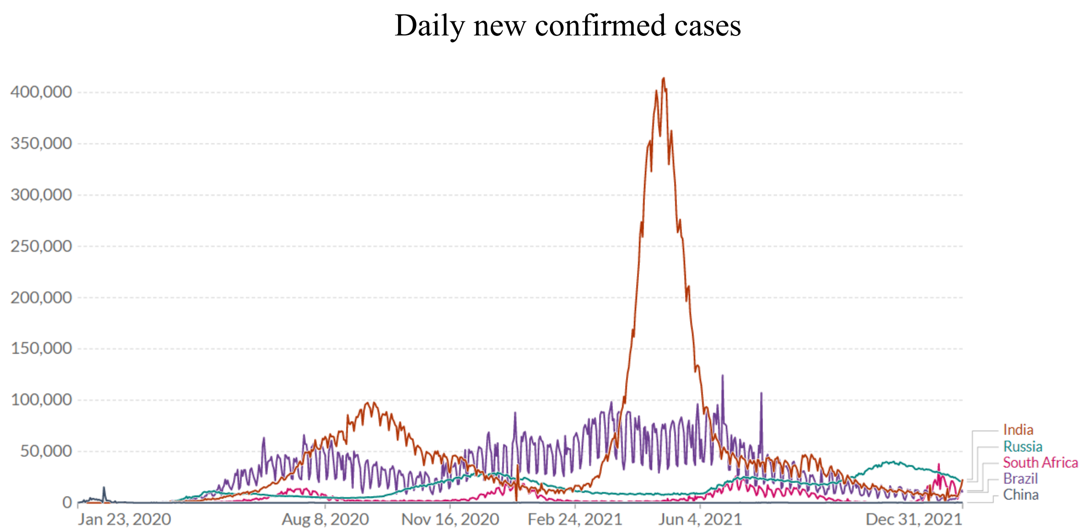


Figure 2 Line Chart of Daily new confirmed COVID-19 cases during the period 01.01.20-31.12.21 (Source: ourworldindata.org)

Figure 2 shows the number of confirmed infection cases per day. With the peak of daily infections already in January, China was the first country affected and the first to respond. The Chinese government soon introduced restrictive measures, including a complete lockdown of Wuhan City, closing social places, and requesting citizens to quarantine at home. As a result, China managed to take the situation under control. When the situation in Europe and America just started to get worse, it began to improve in China, where the state of emergency status of the country was changed again to normalization on March 8th, 2020.

India reported its first confirmed cases on January 30th, 2020, but only starting from March 25th to June 30th the country introduced a five-phase lockdown plan. On September 1st, 2020, India was the country with the highest number of daily new cases in the world (Jiao et al., 2022). This development is clearly visible in Figure 2, where India was also the country with the highest daily reported new cases amongst BRICS countries and has reached its peak of 414'188 cases on March 6, 2021, when India was again the country with the highest number of daily infections in the world. But in terms of cumulative new cases per million of inhabitants (Figure 1), where China (1'439 Mio) and India (1'380 Mio) have the biggest population, the development for India and China looks comparably mild.

Russia reported the first case on March 2nd, 2020. While the country was leading the list of highest number of infections per day for BRICS countries from mid of April 2020, with only few days of Brazil overtaking, Russia reached the peak of the first wave on May 11th, 2020, when numbers started to soften like the development of other European countries, while other BRICS countries continue to grow. The Russian government put their focus on the development of a vaccine and was the first country to announce the release in August 2020. Despite this early introduction, the cumulative number of infections per one million inhabitants remains comparably high and daily infections reach their peak on October 31st, 2021, at 39'931. Russia follows Brazil and takes the second place of the BRICS countries in highest infection compared to its population as of November 10th, 2020.

Also, South Africa only started to first report as of March 5th, 2020. From that day on, the virus started to spread in South Africa and moved faster than in any other country on the continent and on March 26th, 2020, South African government already introduced a full lockdown for 21 days which was further extended. Starting from May 1st, 2020, the country released lockdown from Alert Level 5 to Level 4 (Carlitz, Makhura, 2020). With a population of 59 Mio, the lowest amongst the BRICS countries, South Africa has experienced the highest daily new cases 37'875 on December 12th, 2021, which pushed the country over India in the cumulated comparison.

The Brazilian government - despite of the rapid increase of the first cases in many countries - didn't take the disease seriously and, on the March 11, when WHO declared the global pandemic, was only at the very beginning of reporting its first cases (Statista, 2022). Already on May 14th, 2020, Brazil's cumulative number of COVID cases reached its first million. As the numbers of COVID cases were growing exponentially, soon the country was among the countries with the highest figures worldwide. On June 22nd, 2021, Brazil reached its peak with 124'248 cases on one day. From all BRICS countries, the overall situation of infections compared to the size of the population, Brazil was very fast taking its leading position.

5.2. How does global stock market react to the pandemic outbreak?

The coronavirus outbreak turned out to be not only a health, but also an economic threat, resulting in a recession for many countries, which have faced unprecedented challenges since then. This economic crisis caused by COVID-19, could be considered a unique crisis as it affected all spheres of socioeconomic life. It included deep supply shock, arising from multiple long-term lockdowns in many countries; demand shock, arising from reduction of household spending, increased unemployment, impairment in production and currency devaluation, consumer prices rise and other negative effects.

	Growth rate of real GDP (%)	**Growth rate of GDP** (%) per capita	**Exports** (billions of USD)	**Imports** (billions of USD)	**FDI Inflows** (billions of USD)
2019	2.4	1.3	19019	19290	999
2020	-3.6	-4.6	17619	17828	1530
Annual growth rate			-7.4	-7.6	-35

Table 1: Key figures of the global economies (Source: UNCTAD)

Table 1 illustrates key economic indicators of 2020 and their change compared to the previous year. The rapid spread of COVID-19 had an impact on a global gross domestic product (GDP) as an aggregate measure of production, income, and expenditure of an economy. Despite the forecast of the International Monetary Fund (IMF) in January

Outlook, which was expected the global growth in 2020 up to 2.7%, the COVID shock changed the scenario for 2020 (UNCTAD, 2020). Thus, the global GDP shortened by 3.6% in 2020 or by 4.6% measured by capita, which compares three time more to the reduction caused by the financial crisis in 2008 (UNCTAD, 2021).

The year 2020 was also marked with a significant reduction in global trade, which was before growing continuously over the three previous years (UNCTAD, 2021, p.17). Moreover, the supply chain collapse caused the decline both in export and in import trade. Global export value in 2020 could clearly reflect the impact of COVID-19 at a total of 17.6 trillion dollars, which was 7.4% below 2019 results. A similar picture could be found at global import performance with a reduction of trade by 7.6%. Despite the strong decline, global trade started to recover already in the second half of 2020 after the first major COVID-19 period and already in 2021 reached the pre-pandemic volume (OECD, 2022).

During the COVID-19 spread, also Foreign Direct Investments (FDI) as a reflection of interest of foreign investors took a direct hit. The unprecedented global circumstances led to cancelation or delay of numerous investment project as well as interruption of merges and acquisitions. As a result, FDI dropped in average by 35% in 2020, where the strongest decline of 45% was accounted for in America and 16% in Africa. The only region, which could record growth of FDI inflows was Asia with a growth of 54% (UNCTAD, 2021, p.52).

The commodity price index reported a drop of 16% in the first quarter of 2020. Fuel prices, which make the biggest share in the index, were significantly affected by the crisis, and decreased by 32% in comparison with 2019. However, after dropping to its five-years low in April 2020 the index has shown strong recovery and already one year later in April 2021 fuels prices were significantly higher than in the pre-pandemic period (UNCTAD, 2021, p.56).

The overall decline in economic growth was influenced by low performance of global trade, foreign investments, and commodity prices, but for some countries also currency devaluation played a major role for the economic contraction. The change of currency value against the US dollar caused consumer prices across the world's economies to increase up to 5% and even up to 2400% and 560% in Venezuela and Zimbabwe. The COVID-19 shock shed a light on the weakness of the advanced and developing countries arising from the indebtedness.

Like the overall economy, the financial markets in early 2020 showed stability and the initial news of a contagious disease in China didn't attract any attention of most corporate managers and other market participants until January 22nd, 2020. The WHO held the first conference concerning COVID-19 with the International Health Regulations (IHR) Emergency Committee, but the stock decline in this period was mostly observed only in Asian markets. Likely reasons for the start of their decline could have been the statement of Chinese health authorities about human-to-human transmission of the virus as well as the publication by WHO the first situation report "Novel Coronavirus (2019-nCoV)" (Ramelli, Wagner, 2020, p.7-9). Never-the-less, Shanghai SE Composite Index in China dropped by -3.10% the next day, January 23rd.

Despite the strict preventive measures, the virus was spreading in China and beyond the country's borders. As of late January 2020, the virus arrived in France, Italy, and other European countries and first cases were reported also in the USA. With the rapid international spread, uncertainty started to grow. On February 24th, 2020, the biggest market indices in the U.S. and Europe closed with a significant fall for the first time: S&P 500 Index -3.25%, NASDAQ Composite Index -3.71%, FTSE 100 -3.34, NIKKEY 225 -3.34% (Bloomberg.net). This day was followed by weeks with volatility and declining performance trend.

From March 9th to 16th, 2020, global stock markets experienced significant challenges. This period was associated with the fever of disease according to the time gradation suggested by Ramelli S. and Wagner A.F. (Ramelli, Wagner, 2020, p. 2). March 9th, 2020, became the "Black Monday", when markets closed with results below the results during the financial crisis 2008. The volatility and downward trends caused by the COVID-19 uncertainty was adjoined by a dramatic reaction of the stocks to the price war between

Russia and Saudi Arabia on the oil market. The main financial indices in US showed significant decline: Dow Jones Industrial Index - 7.8%, S&P 500 -7.6% and Nasdaq - 7.3%. Also, key indices in UK, Germany, France, and Spain dropped by nearly 7-8% (BBC, 2020b). After the announcement of the Saudi Arabian government to pump more oil, the price of the international oil benchmark Brent fell by 30% (NPR.org., 2020). As a result, on March 16th, 2020, the Chicago Board Option Exchange's Volatility Index (VIX), also known as fear index, jumped up to its highest point 82.69 since a decade (Wong, 2020). The markets did already reflect the significant risk occurred with COVID-19 virus, which caused the sensitive reaction to the development of the oil prices.

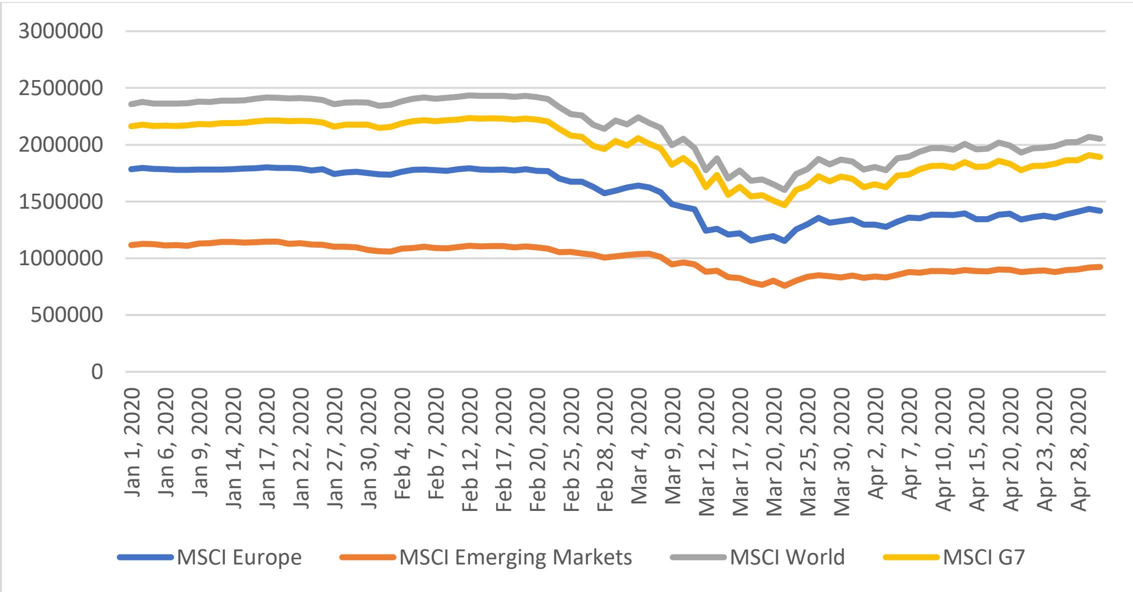


Figure 3: Line Chart of MSCI Indices during the period 01.01.20-30.04.20 (Source: MSCI.com)

Morgan Stanley Capital International (MSCI) Indices, serve as measuring tool for international investors to track performance of global indices. With their variety of indices, they can be used as alternative option to observe the dynamic of a specific area of interest, larger groupings, or the global market. Four indices were selected for this study to display the reaction of global stock markets on COVID-19 outbreak in specific areas: MSCI World (includes 23 countries, also the US), MSCI Europe (includes 15 countries), MSCI Emerging Market (includes 26 developing counties) and MSCI G7 (includes Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States).

Figure 3 illustrates the development of these selected indices within the first four months of 2020. This initial period in 2020 was considered the first wave in many countries and includes incubation, outbreak, and the fever of the pandemic. Thus, exactly within the period from January 1st, 2020, to April 30th, 2020, core market indices dropped to their historical low with overall size of the fall of: Dow Jones -26%, S&P 500 – 24%, FTSI -29%, DAX -29%, NIKKEI 225 -23%, Nasdaq -18% (Senol, Zeren, 2020). The development of the selected MSCI indices all show similar pattern, which follow the timeline of Covid-19 related events: Early declines end of February with the international spread of the virus, stronger declines starting early March up to end of March, when the WHO announced the global pandemic and government responses were engaged.

Only an event with the magnitude of the COVID-19 pandemic had the significance and global spread to create such consistent impact on financial markets, making investors to bear losses and suffer from high level of risk caused by COVID-19.

5.3. Does BRICS economy's reaction to COVID-risk differ?

It would be expected, that if the advanced economies have faced huge challenges, the challenges for emerging countries would be even more enormous. Before the COVID-19 outbreak the growth of the BRICS countries was developing rapidly and in 2018 they were contributing 43.2% to the world's economic growth. Moreover, in 2018 the GDP of BRICS countries even outperformed G7 countries (Guo, Sun, Demidov, 2020). During the COVID-19 outbreak, not only dramatic economic contractions could be recorded, but also recoveries.

The largest contractions among the BRICS countries, except of China, were observed during the second quarter 2020 with the highest GDP growth rates decline in India with -24.4%, then in South Africa -17.5%, in Brazil -10.9% and in Russia -7.8%. Also, China had to experience high decline in GPD with -6.8%, but as it was the first country to feel the impact of the pandemic, their contraction was already recorded during first quarter 2020. For China, this was the only quarter with GPD decrease. From the second quarter on, while others were experiencing the strongest effects, China began to recover and closed the year at an economic growth of 2.3%. Following Chinas example, all BRICS countries started economic recovery in third quarter with India providing positive results in the fourth quarter. (RBI, 2021, p.12-13).

	Growth rate of real GDP (%)	**Growth rate of GDP** (%) per capita	**Exports** (billions of USD)	**Imports** (billions of USD)	**FDI Inflows** (billions of USD)
2019	5.0	4.2	3559	3111	294
2020	0.0	-0.6	3498	2921	251
Annual growth rate			-1.8	-6.1	-15

Table 2: Key figures of the BRICS economies (Source: UNCTAD)

The flat consolidated growth rate (0%) for real GDP in BRICS countries, as shown in Table 2, is therefore highly influenced by the early recovery of the Chinese market, followed by their strong growth performance and the fast-paced recovery of India.

With the global import and export dropping as shown in Table 1, the consequences of COVID-19 on global trade, such as challenges in supply chain and global logistics, reduced availability of raw materials, and restricted productions, a decline in the trade of BRICS countries was expected. Thus, the total trade volumes both import and export in 2020 for all the BRICS countries was down by -8%. In comparison of the results for import and export trade outlined in Table 2, that the reduction in import trade was more significant at a total of $190 billion. The highest contraction both, in import and export trade was indicated by India and South Africa. But again, also in trade, especially in export, Chinas strong recovery offset the decline in other markets. The recovery of other BRICS countries was slower, showed a strong recovery in the first quarter 2021 (RBI, 2021, p.29-30).

With the reduction of export trade, the opportunity to obtain foreign currencies for reserve accumulation was limited but was amounted by borrowings rather than by export earnings

(UNCTAD, 2020, p.5). The contraction was also indicated in the FDI, which declined by 15% in 2020. In contrast to described key figures, reserves, and reserves-to-external debt ratio - as important indicators of macro-financial stability - have shown a fair stability. The reserves of the BRICS countries performed a resilience in 2020 even with a massive increase in China (104 USD billion) and India (80 USD billion) in the second half of 2020, which provided significant import cover. The similar trend was observed in reserved-to-external debt ratio, where almost all BRICS countries achieved a slight increase (RBI, 2021, p.32-34).

Comparing the key indicators, which are illustrated in Table 1 and Table 2, BRICS countries outperformed global economies in 2020 across all areas and managed to get through the crisis with less decline. Despite the obvious economic contractions, which mostly occurred in the first half of 2020, there were still some signs of "green shoots" of economic activity at the end of 2020. The appearances of such rapid recovery in the second half of 2020 were related to government responses, the first easing of COVID measures and continued in first quarter 2021. (RBI, 2021, p.11).

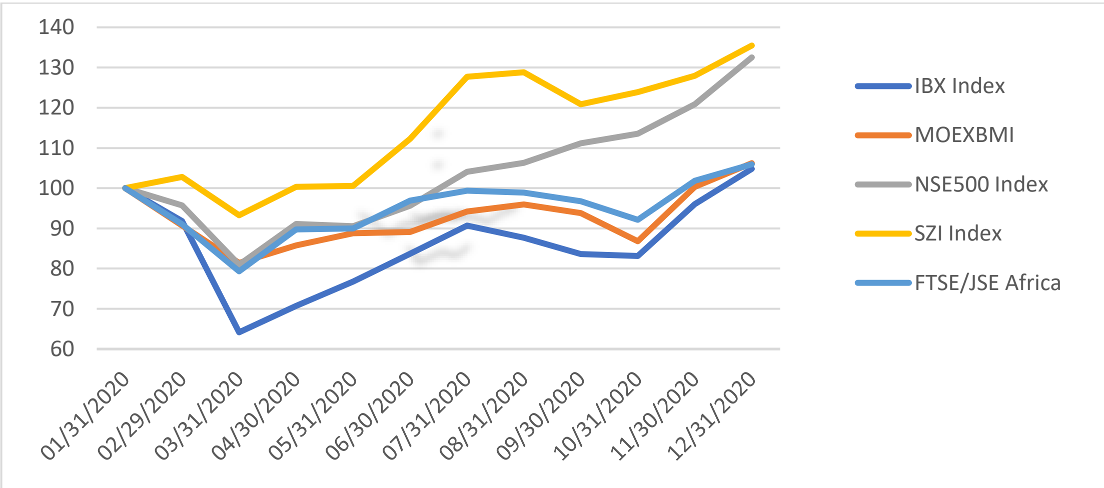


Figure 4: Line Chart of BRICS Indices during the period 01.01.20-31.12.20, normalized by 100 (Source: Own visualization based on Bloomberg database)

Financial markets in BRICS countries initially followed the same effects from pessimistic outlook and concerns of investors about the COVID-19 outbreak like in the rest of the world. Raising number of new infections negatively affected the stock markets of BRICS countries (Figure 4) starting with the decline in February2020, a major drop in March, followed by early recovery as of April.

Data	IBrX Index	MOEX Index	NIFTY500 Index	Shenzhen Component Index	FTSE/JSE Africa all Share Index
01/31/2020	-1.25	1.03	-0.11	2.41	-1.76
02/29/2020	-8.22	-9.33	-6.34	2.8	-8.99
03/31/2020	-30.09	-10.22	-24.25	-9.27	-12.83
04/30/2020	10.27	5.41	14.52	7.62	13.14
05/31/2020	8.52	3.51	-2.38	0.23	0.29
06/30/2020	8.97	0.28	8.34	11.6	7.68
07/31/2020	8.41	5.74	6.62	13.72	2.5
08/31/2020	-3.38	1.89	3.72	0.88	-0.44
09/30/2020	-4.58	-2.26	-0.32	-6.18	-2.18
10/31/2020	-0.55	-7.46	2.57	2.55	-4.75
11/30/2020	15.46	15.61	11.87	3.28	10.46
12/31/2020	9.15	5.86	7.46	5.86	4.06

Table 3: Monthly indices returns within 2020 (Source: Own presentation based on Bloomberg database)

Table 3 provides more detailed information about the stock market reaction of the BRICS economies' main indices and their monthly trends. The stock market of Brazil entered the pandemic period already with negative performance of IBrX Index and was affected most in March 2020, when it was already clear that the outbreak would be difficult to manage, with the monthly decline by -30.09%. For the other BRICS indices March 2020 was also a challenging month, when they showed the highest drop in 2020 (NIFTY500 -24.25%, FTSE/JSE -12.83%, MOEX -10.22%, SZI -9.27%).

However, the immediate recovery in the second quarter among all the indices is shown with positive return rates up until September 2020, when increasing infection numbers indicated a return of the virus. Still, the Indian Nifty500 Index and the African FTSE/JSE Index showed peak growth rates already in April 2020 (14.52% and 13.14% respectively). The sudden turn-around was strongly related to the aggressive fiscal and monetary policy in response to the pandemic announced by G20 leaders and members of the European Union (EU). One of the first measures, which were undertaken to fight COVID-19 effects, was a transfer of $5 trillion from G20 leaders into global economy and Coronavirus

Emergency Aid Packages (CEAP), signed by President Trump (Albuquerque R., et al. 2020, p.7). Efficient market theory (EMT) states, that all available and relevant information will be immediately reflected in the market prices.

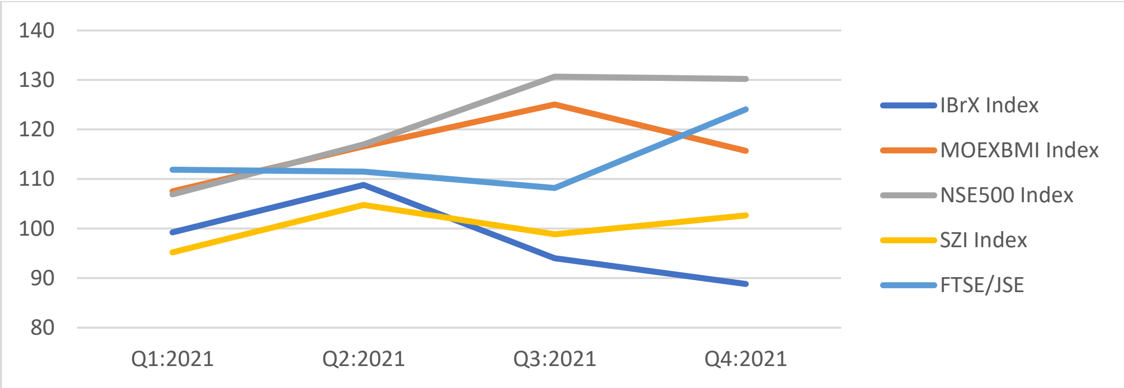


Figure 5: Line Chart of BRICS Indices during the period 01.01.21-31.12.21, normalized by 100 (Source: Own visualization based on Bloomberg database)

Despite the short slowdown in autumn 2020 shown in Figure 4, the monetary and fiscal policies, served their purpose and largely supported resilience and growth also throughout 2021 as shown in Figure 5. In 2021 almost all the BRICS indices performed relatively good resilience, except of the Brazilian index IBrX with a significant drop by -13.61% in third and by -5.51% in the fourth quarter of 2021. Figure 5 depicts that also the Russian index showed some decline at the end of the year by -7.74%. But both, the Chinese, and the South African index have seen positive developments in the fourth quarter 2021 (Bloomberg.net).

The recovery trend and stabilization of financial markets in BRICS countries were highly driven by political, economic, and financial measures, announced by international and national institutions and organizations, to prevent the spread of disease and its negative impact on economics. The detailed description and study of governmental response and monetary and fiscal policies will be discussed in one of the following subsections.

5.4. Is there a link between economic policy uncertainty and stock markets?

Events like the global financial crisis, political conflicts, terrorist attacks and spreading diseases, have raised concerns about policy uncertainty. As a result, the role of policy uncertainty has become more important, which caught the attention of investors, policymakers, and academics. Various empirical studies were investigating the impact of the EPU in notion of fiscal and monetary policy and regulations on macroeconomic and on stock market fluctuations. The research revealed three areas of economic growth, which are negatively affected by the growth of uncertainty: cancelation or delay of investment projects, decrease in consuming power due to increasing savings of householders and decline in financial markets due to the increased volatility (Charnavoki, 2018). Sun, Chen, Wang, and Li (2020, p.7) have found, that important historical political and economic events, such as 2008 Global financial crises and the European sovereign debt crisis in 2011 have enhanced the co-movement between EPU and commodity prices. A range of studies also proofed the negative effect of increasing EPU on investments, employment, and production. And Meinen P. and Roehe O. (2016, p.15-16) have documented negative investment response to the uncertainty shock.

To measure the impact and the role of EPU Baker, Bloom and Davis (2016) developed a new index. Initially this index was targeted to examine the evaluation of the American EPU since 1985. The principle of the index was to reflect the frequency of defined terms in leading newspapers. Over time the scope of the index was expanded and eleven countries, ten of which are part of the G10, were added. To reduce concerns about the reliability of the EPU and its validation index, the founders conducted a range of tests, which proofed a strong relation between their measure of EPU and other measures of economic uncertainty, such as stock market volatility, known as VIX. Adding valuable information and indications to uncertainty, the index soon became widely used by commercial data providers, banks, policy makers and other market participants.

As a consistent and reliable indicator and measure tool for EPU, the index was applied in numerous studies by scholars and researchers to provide causal inference with EPU.

Using micro and macro estimation approaches, Baker et al. (2016, p.1596) found evidence, that the increasing policy uncertainty leads to decline in investments and employments as well as to greater stock price volatility. Similar conclusions have Stock and Watson (2012, p.31-32), namely, that economic shocks and recessions are associated with increasing uncertainty. Therefore, researchers started to also study the overall effects of the EPU on stock markets and their co-movements. Li and Peng (2017) indicated in their research, that US EPU index has a negative effect on China-US stock market correlation and therefore recommend to investors to pay close attention to US EPU to gain diversification benefits. Another important contribution in investigating EPU effects on contagion risk of investment was made by Tsai (2017), whose results show, that EPU in China is the most influential and spread its systematic risk easily. Moreover, the same study indicates that stock markets in emerging countries are influenced by the policies in developed countries. While the effects of EPU on stock markets and the co-movements became clearer, other literature explains the effects of EPU and its various indicators in different sectors, like commodity markets, exchange rate, inflation, or stock market volatility. The results again show, that EPU can have devastating impact on both, the economy as a whole and on specific stock markets.

The COVID-19 disease triggered the largest uncertainty since the Great Depression of 1929-1933, and impacted many aspects of life: healthcare systems, human capital, social regulations and restrictions, recovery after pandemic, government response, impact on businesses and economy (Baker, Bloom, Davis, Terry, 2020). Baker et al. (2020) confirmed the strong relation between EPU and the COVID shock, namely the significant rise in the economic uncertainty during the first quarter 2020. The results of that study indicate that “about half of the forecasted output contraction reflects a negative effect of COVID-19 induced uncertainty”.

Figure 6 depicts the comparative development of the EPU indices for Brazil, Russia, India, China and Global EPU, since the index for South Africa is not available. The global EPU Index was 25% higher in March 2020 than the average level in 2019, when the trade war between China and the USA took place and Brexit was in its final stage. Especially Russia showed the highest level of uncertainty with the start of the pandemic compared to any other BRIC country and even to the global EPU index. The Russian EPU index was two times higher than during the Crimea events in 2014, when the country was sanctioned in trade by the EU and the US. It is quite surprisingly, that despite one of the highest numbers of the new COVID cases, Indian EPU index remains the lowest within the whole observation period.

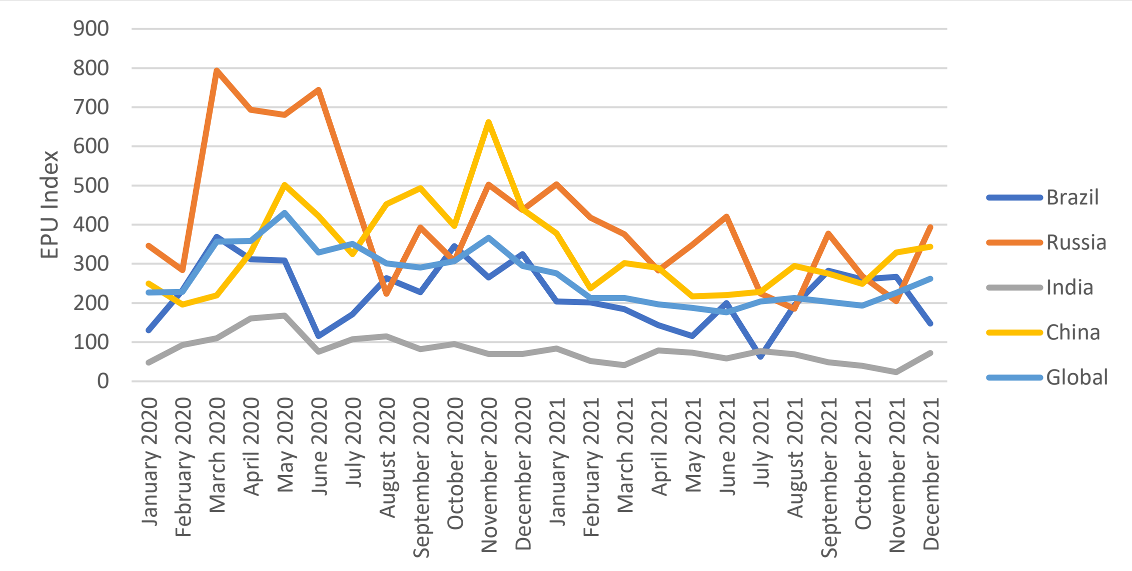


Figure 6: Line Chart of Evaluation of EPU Index during the period 01.01.21-31.12.21 (Source: Own visualization based on the data, obtained from www.policyuncertainty.com)

The timeline of the COVID-19 pandemic is also reflected in EPU indices of BRIC countries and the World. High uncertainty is visible during the first two waves of the pandemic with a decline during the summer months of 2020 and spring months 2021. Considering the relation between EPU, economies and stock markets, the trends of EPU as shown in Figure 6 and of financial markets shown in Figure 3 and Figure 4 reflect the theoretical correlation. But while economic uncertainty tends to grow during crises, it never appears to be the reason of them. However, the impact from increased uncertainty puts increasing focus on recovery and stabilization policies as a response.

5.5. What is the impact of government response?

Governmental response was a comprehensive process, which included social restrictions and control measures as well as fiscal and monetary policy. Co-ordinating the strategy to prevent the spread of the virus among the BRICS countries was one important component of the response to pandemic, but as the history showed, it didn't contain the disease and it continued to spread (Lefifi, 2020, p.14-15). All BRICS countries took different interventions, such as restrictions, healthcare regulations and control measures. Jiao et al. (2022) classified in their analysis the adopted reactions into containment, intermediate and mitigation strategies.

The containment strategy of China, as the first country to deal with Covid-19, was already adopted in the early stage, when the number of new cases sharply increased. On January 23rd, 2020, China completely isolated Wuhan City, closed all public places and enforced locals to stay at home. With a strict execution of the „four early" principle, which relies on early detection, reporting, diagnosing and treatment, the government managed to take under control the spread of the disease and new cases started to decline. On March 19th, 2020, there was no new cases reported in Wuhan and already on May 8th, 2020, China changed emergency status back to normalization. The response strategy, implemented in China, proved itself as efficient. Despite the return to normalization status, the government kept certain measures of control to prevent sporadic cases, expedite medical research and vaccine development. And with the continuous control mechanisms in place, China managed to disconnect from the global turmoil in spring 2020. But despite the rapid response and containment, as the most important global good and equipment supplier, China still experienced a short-term, but significant negative impact of the outbreak (Morales & Andreosso-O'Callaghan, 2020, p.1-14). The required measures to save a nation's health, were at the same time the reason for its economic drop.

The intermediate strategy of India and South Africa combined containment and mitigation strategies implemented in different epidemic phases. Immigration control regulations were taken by India on January 25th, 2020, as first measures to prevent the import of the new cases. Despite strict immigration control new cases started to rise sharply. In March 2020, the Indian government had to implement a five-stage lockdown plan (Jiao et al., 2022, p.17), which included isolation measures, closing of shops and factories, imposed curfews. The first pandemic wave in India lasted until November 2020 with its peak in September 2020. Despite the rapid growth of new cases the easing of several measures were already announced on April 15th, 2020, to support economic activities (International Monetary Fund [IMF], 2021). In June 2020 India launched a four-stage unlock program to restart further economic and social activities. In February 2021, live in India was back to normal without any social distance policies (Jiao et al., 2022, p.4). While the Prime Minister of India announced the biggest vaccination campaign, with the start of a second wave in spring 2021, the government had to announce additional lockdown measures again.

Like India, South Africa started its prevention measures with closing borders and ports in the mid of March, when the first COVID cases, brought by tourists, occurred. On March 26th, 2020, the government announced a nationwide 21-days lockdown at a strictest level five with only critical services being opened. Only starting from May on, some control measures were relaxed, resuming operations and work (Jiao et al., 2022, p.17). The reopening of most economic activities was following the broader relaxation of measures in June 2020, in particular schools' reopening, removing travel and social restrictions, but maintaining healthcare practices. With an announcement of the second COVID-19 outbreak on December 9th, 2020, strict community prevention and control measures were resumed, including closing of the boarders, curfews extension, ban on the sale of all alcoholic beverages. With decreasing cases of new infections, the restrictions were eased starting in February until in May 2021, the third wave began, and restrictions were tightened from level 2 to level 4 implicating already familiar measures, which were taken during the previous waves (IMF, 2021).

The mitigation strategy of Brazil implied that the epidemic spread couldn't be avoided, so its unimpeded spread would only lead to herd immunity. This was also reflected in the passive response of the federal government, who considered that despite the introduction of prevention measures, the normal production activities should be kept, as the reduction of economic activity would cause greater damage, than deaths caused by the disease

(Ventura et al., 2021). On February 3rd, 2020, when the first cases were reported, the Ministry of Health declared a public health emergency. Only basic social prevention and control measures were introduced a little later, which included closing of schools and wearing masks. From March 2020 to December 2020 the pandemic was spreading enormous, and Brazil entered state of public disaster. With its poor medical system and infrastructure, lack of prevention materials and wealth problems, Brazil was suffering to restrain the spread of the virus, especially amongst the poor population, which led to the highest mortality rate among BRICS countries (Jiao et al., 2022, p.7).

Considering their close neighborhood to high-risk countries, the Russian government started its mitigation strategy with closing boarders, first only with China, but then banned foreigners to enter the country (IMF, 2021). Trying to find a compromise between the lockdown of cities and complete lifting of restrictions, the government implemented national paid vacation until May 11th, 2020, to reduce social contact. Although daily new cases in May 2020 exceeded 10’000, restrictions were gradually lifted. Since a national economic recovery plan was implemented by the Russian government, it was considered that the COVID-19 situation is under control and restrictive measures would not be necessary (Jiao et al., 2022, p.4-14).

The prevention measures, in particular lockdown of cities, closing of the boarders, health measures, aimed to stop or to slow down the spread of pandemic, but at the same time they lead to economic depressions and affect financial market. As some studies have shown, national Corona-related measures, in particular tightening of the national lockdown restrictions lead to a negative stock market return, even if this effect was delayed, and the easing of lockdown restrictions had a positive impact on the market (Scherf et al., 2022).

The COVID-19 crisis with its consequences was a substantial shock for BRICS countries, but to recover from its impact, policy reaction was needed (Zhang, Hu, Ji, 2020). The fiscal policies of the BRICS countries were applied towards the funding of the immediate heath response, including strengthening of the health sectors, and direct support of households and businesses. To achieve their targets following key fiscal instruments were applied: tax deferment, preferential credits, direct financial support of vulnerable groups, emergency credits and subsidized mortgage payments and interests (RBI, 2021).

Besides large stimulus packages provided in frame of the fiscal policies, vulnerable businesses were supported by BRICS countries central banks with additional measures within monetary policy. Thus, the banks set the policy rate at historical low level to ensure continued accommodative monetary conditions. Furthermore, implementing various instruments, like special swap and credit lines, open market operations, maintained both, liquidity in domestic and foreign currencies and credit flow (RBI, 2021).

Brazil's government injected in total \$105 billion of stimulus packages into the economy to combat the effect of the pandemic, in particular its primary deficit of 7.2% GDP. From August 2020 until March 2021, the central bank lowered the policy rate to it historical low at 2%. The Monetary and fiscal measures also included, but were not limited to reduction of reserve requirements, expansion of health spending, direct transfers to low-income population, expansion of credit lines for businesses and households and employment support programs, which were extended to the second quarter of 2021 (IMF, 2021).

Russia implemented fiscal measures by providing total packages of USD 89 billion in 2020, which made 6% of its GDP, additional USD 17 billion were planned for 2021 (RBI, 2021). Other measures included compensation for medical staff, sick leave and unemployment benefits, lump-sum benefit for children of different ages, tax holidays, wage contributions and budget grants for small and medium enterprises (SME) in affected sectors. Other than that, the Central Bank of Russia (CBR) decreased the policy rate to the historic low rate of 4.25% in July 2020, but started to increase it again in March 2021. Aiming to support SME, refinancing facility, and forbearance on provisioning for restructured loans was introduced by CBR (IMF, 2021).

India implemented USD 23 billion relief packages to support the country's industry, of unorganized or unformal businesses, which employ 94% of the country's population (Lefifi, 2020, p.14-15). The fiscal support measures were divided by India's central government into two groups; the first, above-the-line measures (4.1% of GDP) aimed to provide social protection and healthcare; the second group, below-the-line measures (about 5.3% of GDP) focused on business and credit provision support (IMF, 2021). The Indian government approved a budget for 2021-2022 with 34.5% increase in capital and 137% in healthcare expenditure (RBI, 2021). Within the monetary policy the Royal Bank of India (RBI) introduced liquidity measures, which included comprising Long Term Repo Operations, a Cash Reserve Ratio cut and open market operations (IMF, 2021).

China indicated in the first quarter of 2020 the first negative growth rate since 1992. To boost the economy, the Chinese government injected RMB 4.9 trillion, which made 4.7% of its GDP, and were aimed to increase spending on epidemic prevention and control, production of medical equipment, accelerated disbursement of unemployment insurance, tax relief and social security contributions. A range of monetary policy measures were taken to maintain financial market stability: liquidity injection into the banking system via open market operations, expansion of re-lending and re-discounting facilities, reduction of reverse repo rates for SMEs. The government also implemented multiple measures to ease the financial conditions of affected households and corporations through encouraging lending to SMEs, delay of loan payments and increase bond issuance by corporates (IMF, 2021).

The South African economy was already in recession when it entered the pandemic phase, and since a steep depression was predicted, some rating agencies downgraded its sovereign credit rating to BB from BB+ (Lefifi, 2020, p.14-15). To combat the impact of COVID crisis the South African government provided economic support package of R 500 billion, which makes 10% of its GDP, focused on help to households, affected companies and their employers. In March 2020 the central bank of South Africa announced measures to ease liquidity conditions and reduce the policy and repo rate, provide debt relief to bank's borrowers and purchase government securities in the secondary market (IMF, 2021).

The outlined control, monetary and fiscal policy measures implemented in BRICS countries during the time of the COVID-19 spread significantly differed in selection, in value and efficiency. As such, China has managed to take the spread of the virus under control immediately and therefore it conducted its fast recovery. Both India and Brazil were gradually boosting their economies and were on the confident way of recovery. In opposite to them, Russia and South Africa were struggling to achieve a pre-pandemic economic level.

Government interventions made during the economic crises are necessary measures, though they may have positive and negative impact on various aspects of a country's society, economy, and financial markets. According to the efficient market theory, introduced by Eugene Fama, current market prices immediately reflect all available and relevant information (Volkart & Wagner, 2018, p. 247-251). In this sense, restrictive interventions would increase uncertainties and create economic hurdles, which would cause increased investors' concerns and would therefore show economic decline, while fiscal and monetary interventions and the easing of restrictions cause the opposite result. This would imply that government response policy is reflected in stock market performance and a considerable variable for this study.

6. Data

In this section dependent and independent variables, which are used for the analysis, will be described and its descriptive statistic is presented.

6.1. Stock Indices and Returns

All data of stock markets for this study were obtained from Bloomberg (Bloomberg L.P., 2022). Since the research investigates the returns of BRICS stock markets, the indices as shown in Table 4 were selected.

Brazil	IBrX 100 Index
Russia	MOEX Index
India	NIFTY 500 Index
China	SZI Index
South Africa	FTSE/JSE Africa all share Index

Table 4: Main indices of the BRICS countries

IBrX 100 Index (Bloomberg ticker: IBX) – Sao Paolo Stock Exchange Index. The Brazil IBrX 100 Index is a total return index that measures the return of a theoretical portfolio composed of the top 100 most actively traded and best representative stocks on BOVESPA. Stock prices are quoted in Brazilian real (BRL). On the day of obtaining the data, there were 98 components in its list (Bloomberg.net). The market capitalization as of December 31st, 2021, was reported at 3’516’015.56 Mio. BRL / 631’071.63 Mio. USD (Bloomberg.net).

MOEX Russia Index (Bloomberg ticker: IMOEX) – is a cap-weighted composite index calculated based on prices of the most liquid Russian stocks of the largest and dynamically developing Russian issuers presented on the Moscow Exchange. The number of the index constituents may vary but should not exceed 50. On the day of obtaining the data, there were 43 components in its list. Stock prices are quoted in Russian ruble (RUB). MOEX Russian Index was launched on September 22nd, 1997, at base value 100 (Bloomberg.net). The market capitalization as of December 31st, 2021, was reposted at 56’235’332.23 Mio. RUB / 749’034.42 Mio. USD (Bloomberg.net).

NSE NIFTY 500 Index (Bloomberg ticker: NSE500) – capitalization-weighted index of 500 companies, that represents about 90% of the total market capitalization of India and about 98% of total turnover. The index was developed with a base value of 1000 as of 1994. The index is quoted in Indian rupee (INR). On the date of obtaining the data, the index listed 501 components (Bloomberg.net). The market capitalization as of December 31st, 2021, was reposted at 242’222’600.1 Mio of INR / 3‘251‘493.77 Mio. USD (Bloomberg.net).

Shenzhen Component Index (Bloomberg ticker: SZI) is a Shenzhen Stock Exchange (SZSE) Component Index in a free-float market cap-weighted Index. The constituents consist of the 500 largest and most liquid A-share stock listed and traded at SZSE. The index was developed with a base value of 1000 as of July 20th, 1994. The index is quoted in the Chinese Yuan (CNY). On the date of obtaining the data, the index still listed 501 components (Bloomberg.net). The market capitalization as of December 31st, 2021, was reposted at 26’940’526.44 Mio of CNY / 4’238’530.93 Mio. USD (Bloomberg.net).

FTSE/JSE Africa all Share Index (Bloomberg ticker: JALSH) is a market capitalization-weighted index and was launched June 24th, 2002. Companies included in this index make up the top 99% of the total pre-free-float market capitalization of all listed companies on the Johannesburg Stock Exchange. The index is quoted in South African Rand (ZAR). The constituents consist of the 143 largest and most liquid stocks. The market capitalization as of December 31st, 2021, was reposted at 17’375’361.81 Mio of ZAR / 1’090’519.85 Mio. USD (Bloomberg.net).

Among the BRICS countries the indices with the biggest weight are Shenzhen Component Index (42.55%), NIFTY 500 Index (32.64%), FTSE/JSE Africa all Share Index (10.95%). And the smallest weight has IBrX 100 Index (6.34%).

For the study, dividend adjusted historical price data was used. Though there are no strict regulations to look at historical prices, but dividends can affect the price of the underlying stock (Ruppert, Matteson, 2015, p.7-8). Companies, which are stable and performing good, usually pay out dividends to distribute profits to shareholders. On the declaration date, when dividends are announced, the market already assumes this payoff and the prices may go up. However, on the ex-dividend date or right after, investors are not entitled to a dividend, so the stock price will be adjusted downward by that number of dividends. In this perspective, if the price date is not dividend-adjusted, that can understate results. To avoid negative historical prices, some market platforms like Bloomberg adjust the closing prices and therefore neutralize the effect of dividends pay-out.

Most of the studies and researches apply asset returns instead of asset prices because of two reasons. First because stock returns are the better measurement of the investor’s profit or loss and secondly, return series have more attractive statistical properties. Price series are usually nonstationary, what can lead to poor understanding and forecasting. And on contrary, returns are more likely to mean revert, because they are distributing randomly around zero mean (Tsay, 2010). Thus, I have employed returns into the analysis of market indices instead of prices. Still, the stock returns will be tested for stationarity in section Methodology and Research Design. Also, daily dataset provides better information than monthly data and tends to ascertain the robustness of the outcomes regarding a particular hypothesis (Bannigidadmath, Narayan, 2016). Also log returns are commonly used in financial time series. Therefore, returns of daily indices were calculated as the difference between the daily natural logarithm return. The calculation is shown in the following equation:

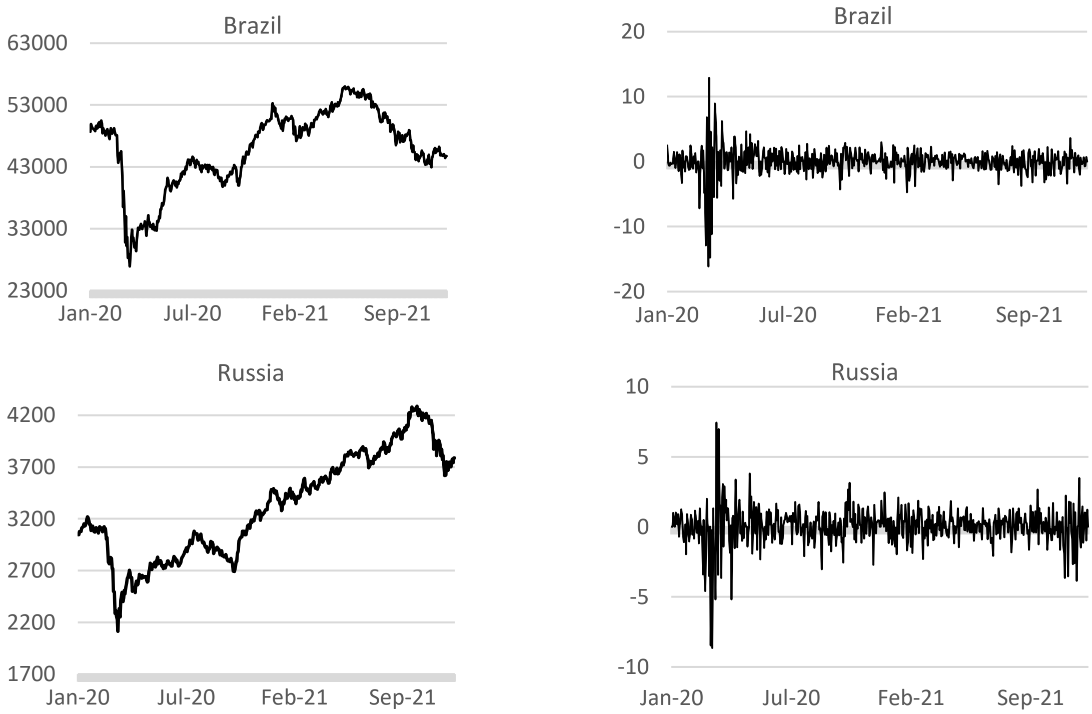
$$r_t = ln\, P_t - \ln P_{t-1}$$

Equation 1: daily stock returns

where r_t is a stock return at time t

P_t and P_{t-1} are the closing prices at time t

Figure 7 shows the graphical represantation of the time series plot of stock indices and stock returns. There is a clear trend of 523 daily observation prices of the specified stock indices from January 1st, 2020, to December 31st, 2021. When daily prices converted into log returns, the plots in Figure 7 (right panel) illustrate, that there are large negative values especially in March 2020. All plots show the evidence, that there is a volatility clustering in daily returns of stock markets.



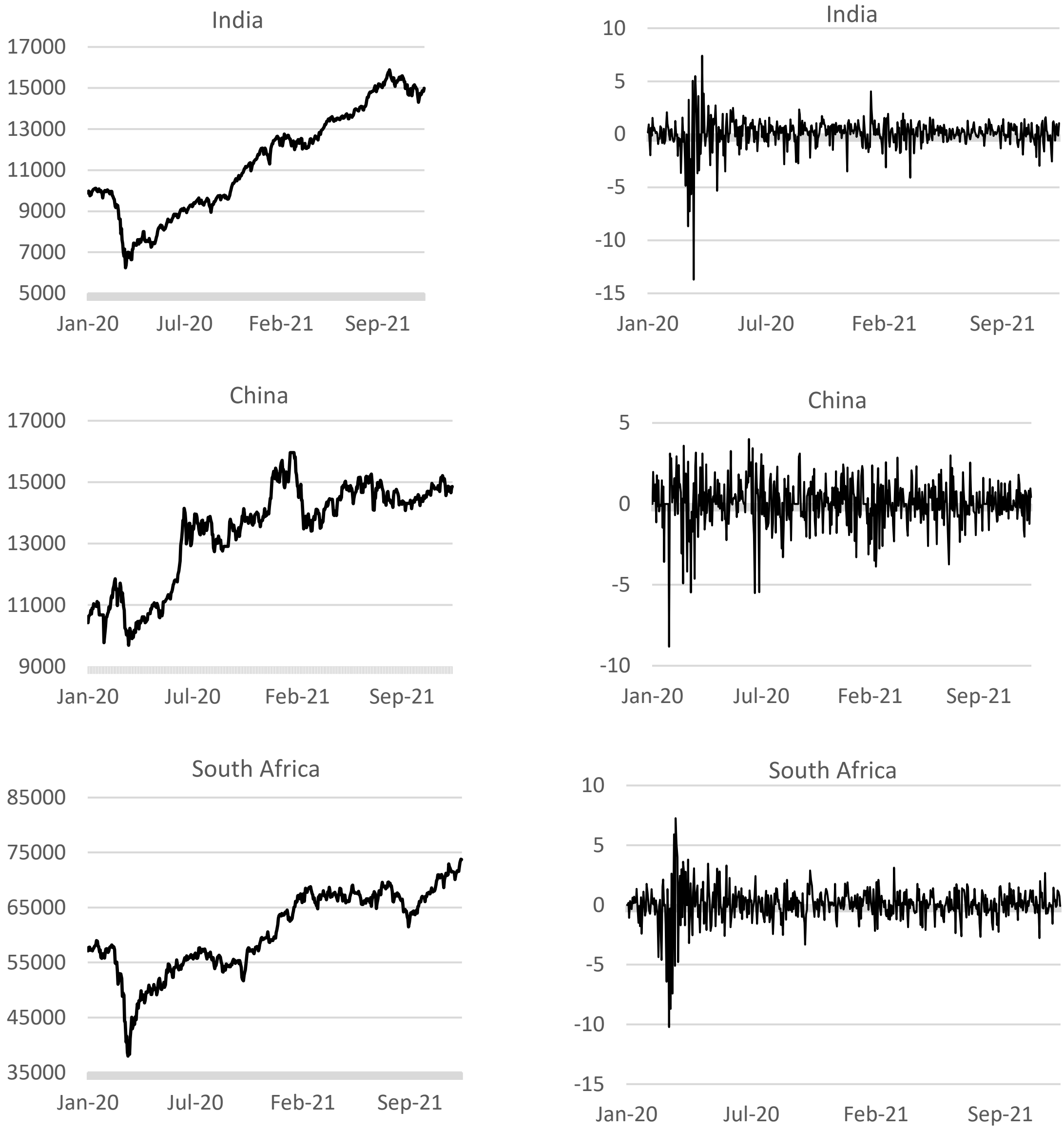


Figure 7: Results of daily prices of observed stock indices (left panel) and their daily returns (right panel)

6.2. Independent Variables

COVID-19 PROXY

The coronavirus crises caused by severe respiratory syndrome SARS-CoV-2 virus appeared as public health and economic threat. Its infectious disease was first detected on December 31st, 2019, the first cases of pneumonia, which were detected in Wuhan, China, were reported by the World Health Organization (WHO) China Country Office. On February 11th, 2020, the disease was first called a pandemic, and the following month it was also officially classified as such. It was rapidly spreading across 233 countries and territories, wreaking havoc on stock exchanges and financial sectors across the globe (WHO, 2022). The pandemic triggered a decrease of global annual growth by 2.5 percent, which is assumed to be a recessionary threshold for the global economy (UNCTAD, 2020). The number of confirmed cases of infections was growing at a tremendous rate and soon reached in BRICS countries a total of 22.1 million at the end of December 2020 and of 71.2 million at the end of 2021. The spreading of COVID-19 cases across the observed countries is illustrated in Figure 1, demonstrating the differences in cumulated COVID cases in BRICS countries.

The data, specifically daily confirmed cases and daily mortality cases was obtained from the World Health Organization website. For this research the daily growth rate of cumulative cases was used as measure of COVID proxy for a particular country. To match COVID-19 variables to the daily stock return data, the data on weekends was omitted. The daily COVID-19 cases were found to show a high degree of non-stationarity. To remove it, the data was measured on a daily growth rate basis. More specifically, for each economy *c* in a day *t*, COVID-19 cases were computed as follows:

$$COVID19_{c,t} = \left(\frac{(cumul.cases_{c,t} - cumul.cases_{c,t-1})}{cumul.cases_{c,t-1}} + 1\right)$$

Equation 2: growth rate of cumulated daily new cases

For measuring the subsequent independent variable of COVID mortality cases, the same calculation for the daily growth rates was used.

ECONOMIC POLICY UNCERTAINTY INDEX

The aim of the analysis is also to test if there is a significant impact of the economic policy uncertainty (EPU) on BRICS' stock markets. The EPU index for each observed country for the period of 2 years from January 2020 till December 2021 was obtained from the website https://www.policyuncertainty.com. The index data is available at a monthly frequency. To match EPU Index to daily stock, the monthly value of the index was placed for each day of the corresponding month. Considering that the EPU Index was not available for South Africa, instead the Global EPU Index was used as representation for the model. The dataset of the Global EPU Index was only available until November 2021. For that reason, the model's period was shortened by one month.

GOVERNMENT RESPONSE INDEX

In addition to COVID cases and EPU Index, the analysis also measures the effect of the overall government response on the stock return of BRICS' markets. Governments were assuming a series of measures to response the COVID-19 outbreak. Therefore, the Oxford University has developed the Covid-19 Government Response Tracker (OxCGRT), which collects information on policy measures to COVID-19 outbreak. The tracker is valid for 180 countries and contains 23 indicators, which are organized in the following five groups (BSG, 2021):

C – containment and closure policies (such as school closures and restrictions in movement)
E – economic policies (e.g. foreign aid and income support for citizens)
H – health system policies
V – vaccination policies
M – miscellaneous policies

For the analysis the overall government response index (GRI) was used, which reflects all indicators in the database and is changing over the timeline of the COVID outbreak. The OxCGRT dataset was obtained from GitHub repository (GitHub, 2022). To stabilize the variance and reduce the effects of interventions, natural logarithm transformation is also applied to this variable.

6.3. Descriptive Statistics

The Table 5 presents the summary statistics of the 523 daily observations for the index stock returns and other independent variables, which are used in the regressions.

Indices	n	mean	sd	median	min	max	skewness	kurtosis
IBrX Brazil	523	-0.016	2.156	0	-16.120	12.887	-1.608	16.048
MOEX (Russia	523	0.042	1.350	0.120	-8.643	7.437	-0.857	9.371
NIFTY 500 India	523	0.084	1.460	0.160	-13.708	7.409	-2.277	20.338
Shenzen Component China	523	0.068	1.436	0.003	-8.825	4.008	-0.918	3.902
JALSH Africa	523	0.047	1.477	0.032	-10.227	7.262	-1.160	9.737
GR cum. CC Brazil	523	0.029	0.086	0.004	0.000	0.924	6.001	46.031
GR cum. CC Russia	523	0.003	0.099	0.005	0.000	1.050	6.452	50.129
GR cum. CC India	523	0.033	0.117	0.004	-0.511	1.609	7.627	84.868
GR cum. CC China	523	0.020	0.143	0.001	0.000	2.420	12.279	176.982
GR cum. CC Africa	523	0.026	0.074	0.003	0.000	0.963	6.561	60.473
GR cum. MC Brazil	523	0.025	0.102	0.004	0.000	1.386	8.620	89.142
GR cum. MC Russia	523	0.023	0.073	0.007	0.000	1.099	8.863	103.529
GR cum. MC India	523	0.025	0.074	0.003	0.000	0.811	6.625	53.197
GR cum. MC China	523	0.017	0.096	0.000	0.000	1.149	8.224	76.762
GR cum. MC s Africa	523	0.022	0.073	0.004	0.000	1.099	9.511	115.658
Ln GRI Brazil	523	0.105	1.303	0.000	-6.250	11.980	3.342	30.726
Ln GRI China	523	0.140	2.166	0.000	-13.020	19.790	3.296	32.854
Ln GRI India	523	0.110	1.586	0.000	-11.200	14.070	2.995	30.521
Ln GRI Russia	523	0.128	2.116	0.000	-16.660	15.360	0.973	28.127
Ln GRI South Africa	523	0.105	2.112	0.000	-11.660	22.390	3.465	39.936
GR EPU Brazil	523	0.305	18.325	0.000	-192.827	136.647	-0.801	50.655
GR EPU China	523	0.038	6.594	0.000	-92.603	50.723	-3.246	92.610
GR EPU India	523	0.110	35.443	0.000	-260.592	509.766	4.845	98.658
GR EPU Russia	523	0.179	22.044	0.000	-222.704	265.031	1.998	73.284
GR EPU South Africa	523	-0.433	13.855	0.000	-222.524	128.152	-7.138	147.435

Table 5: Descriptive Statistics dependent and independent variables within the period 01.01.20-31.12.21

Notes: growth rate of the cumulated new reported COVID cases (GR cum.CC), growth rate of cumulated new mortality cases (GR cum.MC), growth rate of economic policy uncertainty index (GR EPU) and the natural logarithm of government response index (LN GRI).

Within the timeframe of two years, almost all indices' return, except of IBrX index of Brazil, have positive mean which ranges within 0.04% - 0.08%. Indicated -0.02%

negative mean of IBrX Index should have attracted the attention of policymakers to stabilize it to an appropriate level. It can be seen, that both minimum (-16.12 %) and maximum (12.89 %) return values occurred in IBrX Index. Hence the standard deviation of the IBrX Index has the biggest values. All the returns were negatively skewed, indicating that the tail is on the left side of the distribution. In other words, all of the indices return have a distribution, that is skewed to the right. This can be further interpreted, that the average of each return is smaller than its median. Kurtosis was used to measure the outliers in each tail. All the kurtosis values are large, which shows the evidence that all the returns can be characterized as leptokurtic distributions. As a consequence, it can be described as variables having fatter tails vs. the normal distribution. Also, none of the skewness or kurtosis values point at a normal distribution (Auer, Rottmann, 2015, p.219). The highest growth rate of the daily new cases is 2.42 and reported in China while the lowest 0.92 is indicated in Brazil. Despite the lowest rate of new reported cases, Brazil has the highest growth rate of the daily mortality cases (1.39). The lowest mortality rate is shown in India (0.81).

7. Methodology and Research Design

Choosing the right statistical model is an important part of any research as it should take into account the specific characteristics of the data, which is analyzed. The specific feature of financial time series such as asset returns is, that they contain an element of uncertainty or - as a consequence - volatility, which is fluctuating with time.

7.1. Stationary time series models (ARMA-model)

There are some econometric models to test floating components and volatility components of financial time series. For modelling the floating mean of an asset return r_t it is common to use an autoregressive (AR) model, moving average (MA) model or mixed autoregressive moving average (ARMA) model. These simple models explain the linear relationship between r_t and the prior to time t information, which can include the historical value of r_t and other information about economic environment (Tsay, 2010, p.29).

The autoregressive model *AR (p)* is a form of regression, where p represents the order of autoregressive process and the current value of return depends on its previous values of lag p and a random error. The model can be generally formulating as (Tsay, 2010, p.38):

$$r_t = \mu + \varphi_1 r_{t-1} + \varphi_2 r_{t-2} + \cdots + \varphi_p r_{t-p} + a_t$$

Equation 3: Autoregressive Model

Where: μ is a constant

$\varphi_1 \ldots \varphi_p$ are parameters of the model
a_t is a white noise with a mean zero and variance σ^2

The Moving Average model *MA (q)* represents a linear combination of the past values of the white noise series, where q refers to the lag order of the random error. The general form of the moving average process can be defined as (Tsay, 2010, p.58):

$$r_t = \mu + a_t - \theta_1 a_{t-1} + \theta_2 a_{t-2} + \cdots + \theta_q a_{t-q}$$

Equation 4: Moving Average Model

Where: μ is a constant

$\theta_1 \ldots \theta_q$ are parameters of the model
a_t is a white noise with a mean zero and variance σ^2.

The Autoregressive Moving Average model ARMA (p, q) is a combination of the two previous described models, but compared to them, it requires less parameters for estimation, which can be considered as an advantage of the model. The model was introduced by Box, Jenkins, and Reinsel in 1994 and was expressed as (Tsay, 2010, p.64):

$$r_t = \mu + \sum_{i=1}^{p} \varphi_i r_{t-1} + a_t - \sum_{i=1}^{q} \theta_i a_{t-1}$$

Equation 5: Autoregressive Moving Average Model

Where: μ is a constant

φ_i and $\theta_i$are parameters of the model
p and q are nonnegative integers of the order

a_t is a white noise with a mean zero and variance σ^2.

The model can be interpreted as that the current value of return depends on past value of lags p and on both current and past lags q of random errors.

Since the paper focuses on examining the significance of the independent variables listed in the previous chapter, the ARMA model will be extended with the exogenous (or explanatory) variables $x_{i,t}$. In principle the extended model ARMA is a linear regression model, which uses an ARMA-type process and can be formed as (Tsay, 2010, p.175-176):

$$r_t = \mu + \sum_{i=1}^{p} \varphi_i \, r_{t-1} + a_t - \sum_{i=1}^{q} \theta_i \, a_{t-1} + \pi_1 x_{1,t} + \pi_2 x_{2,t} + \cdots + \pi_i x_{i,t}$$

Equation 6: Autoregressive Moving Average Model Extended

Where: π_i is the coefficient value for the I exogenous input variable

$x_{i,t}$ is the exogenous variable at time *t*

All above-described models assume, that random errors have a constant unconditional mean and variance. But in fact, volatility of the financial time series is time-evolving. Moreover, financial time series include following stylized facts:

- Stock prices are usually nonstationary, whereas in contrast the log stock returns are stationary
- Autocorrelation of returns is sufficiently small and doesn't differ from null
- The occurrence of volatility clustering, which means that the periods of high and low volatility can be remained for certain time period.
- Returns' distribution usually has "fat tails"
- Leverage effects (different reaction of volatility to price increase or drop) (Artamonov et al, 2021, p.72).

7.2. Conditional heteroscedastic models (GARCH-model)

None of the above-described models for floating conditional mean take these stylized facts into account and therefore they are not appropriate models for estimating stock returns. To model time varying volatility, namely conditional standard deviation of an error a_t, autoregressive conditional heteroscedastic (ARCH) was first proposed by Engle (1982). The simple ARCH (m) Model with m lags of shocks, can be formulated as:

$$\sigma_t^2 = \omega + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2$$

Equation 7: Autoregressive Conditional Heteroscedastic Model

Where $\omega > 0$ and $\alpha_i \geq 0$ for $I > 0$.

α_1 and α_m are parameters of the model.

The structure shows, that the model tends to assume a large number of past square shocks a_{t-i}^2. Therefore, as the model requires the estimation of many parameters, it is inconvenient to use. In 1986 the ARCH-model was extended to generalized autoregressive conditional heteroscedastic (GARCH) by Bollerslev (Tsay, 2010, p.110), which implies more flexible and economical specification. The GARCH (m,s) model can be defined as (Tsay, 2010, p.132):

$$a_t = \sigma_t \epsilon_t \,,$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{m} \alpha_i \, a_{t-1}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2$$

Equation 8: Generalized Autoregressive Conditional Heteroscedastic Model

Where a_t is a time series

ϵ_t is a white noise with mean zero and variance 1

$\omega > 0$ and $\alpha_i \geq 0$ for $I > 0$, $\beta_j \geq 0$, and $\sum_{i=1}^{\max(m,s)}(\alpha_i + \beta_i) < 1$

α_i and β_j are parameters of the model.

As reflected by the formula, the conditional variance represents the weighted average of long-run variance ω and lags of square shocks a_t^2 and lags of variance σ_t^2.

Despite the big variety of the ARCH family models the GARCH (1,1) has the biggest success among researchers by empirical analyses. Although it has some drawbacks as it does not take into account any leverage effect and the inability to explore forth Moment for investigating tails and others, the model is still widely used as an etalon (Artamonov, et al., 2021, p.82-83). The GARCH (1,1) model can be written as:

$$\sigma_t^2 = \omega + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Equation 9: GARCH (1,1) Model

The GARCH model can be decomposed in three parts:

- constant parameter ω, which determines the level of long term average volatility.
- squared shock (new information) at time *t* (α), which measures the reaction of conditional volatility to market shocks. When α is relatively large (e.g. above 0.1) then volatility is very sensitive to market evens.
- conditional variance at time *t* (β), which measures the persistence in conditional volatility irrespective to anything happening in the market. When β is relatively large (e,g, above 0.9) then volatility takes a long time to die out following a crisis on the market.

The explanation of the coefficients refers to Alexander C. (2008).

For the estimation of mean of returns different approaches can be applied:

- zero
- constant (which should be estimated)
- simple autoregressive model like AR(1)
- ARMA model
- and others (Salikhov, 2020)

Investigating the reaction of BRICS's stock returns on COVID outbreak, the ARMA(p,q)-GARCH (m,s) model was chosen, as it comprises all essential components, which characterize financial time series in particular conditional mean, conditional variance and shock. Because the examined time series is impacted by exogenous causes, the exogenous variables are incorporated in the time series model, both in mean and volatility equation. That will give the model an ability to quantify the impact of external influences. In the next sections, the best parameters for the ARMA model will be selected and for the heteroscedastic part, the GARCH (1,1) model will be used, since it proved itself as the most reliable standard model of volatility (Artamonov, et al., 2021, p.82).

7.3. Stationarity Test

The time series analysis is based on stationarity, which means time-invariant, behavior. For example, stock returns can differ from previous year, but in contrast to stock prices, their mean, standard deviation are often similar over the years. Time series are considered to be stationary when they meet following conditions:

- $E(r_t) = \mu$
- $Var(r_t) = \sigma^2$
- $Cov(r_t, r_{t-1}) = \gamma\ell$

Where mean and variance are constant and covariance of r_t, r_{t-1} depends only on lag ℓ or in other words lag-ℓ autocorrelation of r_t (Ruppert, Matteson, 2015, p.307-309).

To test the stationarity of the stock returns' time series and other independent variables, which are added to the model, the augmented Dickey-Fuller (ADF) unit-root test is employed. The ADF test is an expanded form of the Dickey-Fuller test, which checks if there is a unit root (root = 1) in the autoregressive process of the first order. The null hypothesis (H_0) of the ADF test states: there is a unit root in data and thus time series is nonstationary. And alternative hypothesis (H_0) postulates the opposite, the time series is stationary (Tsay, 2010, p.76-77). However, only after natural logarithm transformation in the time series of index returns and GRI and after transforming COVID new reported cases, mortality cases and EPU, the results proved the stationarity of both dependent and independent variables. The results of the ADF test are demonstrated in Table 6.

The results show that ADF test statistics are very small, and p-value is less than 5% levels of the test's critical values and hence we can reject the null hypothesis and classify the time series as stationary.

Variables	*t-stat*	*p-value*
BRAZIL		
Ln return IBrX	-5.977	0.01
GR cum. Covid cases	-4.215	0.01
GR cum. Mortality cases	-4.599	0.01
GR EPU Index	-7.481	0.01
Ln GRI	-5.570	0.01
RUSSIA		
Ln return MOEX	-7.220	0.01
GR cum. Covid cases	-4.159	0.01
GR cum. Mortality cases	-4.262	0.01
GR EPU Index	-7.488	0.01
Ln GRI	-8.397	0.01
INDIA		
Ln return NIFTY 500	-5.976	0.01
GR cum. Covid cases	-5.566	0.01
GR cum. Mortality cases	-3.825	0.02
GR EPU Index	-7.471	0.01
Ln GRI	-6.286	0.01
CHINA		
Ln return Shenzhen Component	-8.248	0.01
GR cum. Covid cases	-9.309	0.01
GR cum. Mortality cases	-5.972	0.01
GR EPU Index	-7.476	0.01
Ln GRI	-6.330	0.01
SOUTH AFRICA		
Ln return FTSE/JSE Africa all share	-8.005	0.01
GR cum. Covid cases	-6.951	0.01
GR cum. Mortality cases	-4.374	0.01
GR EPU Index	-7.693	0.01
Ln GRI	-5.420	0.01

Table 6: ADF Test results

7.4. Autocorrelation test for residuals

In the classical finance theory, in particular in the CAPM model, it is assumed that the stock return r_t is not predictable and therefore has no autocorrelations. However, depending on the frequency and method of the calculation of returns they may perform autocorrelations in financial time series. In order to check the efficient market assumption, a number of the statistical tests are used (Tsay, 2010, p.34). A widely used one is Ljung-Box test, which checks, if there are patterns in the series or if it is random. Moreover, it is a comprehensive test to define, if the covariance of a set of correlations lags, and not only one lag, significantly different from zero (Hyndman, 2001). Thus, the null hypothesis for this test postulates:

H_o: the stock return series is not autocorrelated and therefore the series is a white noise
H_1: the series exhibit serial correlation and therefore are not random.

It is considered that the usual significance level of the test is 5% and when p-value is less than 0.05 the null hypothesis is rejected (Ruppert, Matteson, 2015, p.311-314). The results of the Ljung-Box test for the BRICS countries indices in this study are shown in Table 7.

	Chi-Square	DF	p-value
IBrX Index	85.329	7	<0.0001
MOEX Index	21.278	7	0.003379
NIFTY 500 Index	53.225	7	<0.0001
Shenzhen Component Index	2.0479	7	0.9571
FTSE/JSE Africa all share Index	26.915	7	<0.0001

Table 7: Autocorrelation Ljung-Box Test results of index returns

The p-value of four test statistics (Brazil, Russia, India and South Africa) are less than 0.05 for the lag order 7, which is implying that the null hypothesis is rejected, and it is suggested that the daily index returns are significantly correlated. The test results of the Chinese Index don't indicate the presence of serial correlation in the data and thus we will need to fit the ARMA model to correct this problem. Although the return correlation seems to be generally small, the return time series can exhibit volatility clustering, which will be checked in the next subsection.

7.5. Heteroscedasticity test

An integral part of the GARCH model selection as well as ARMA (p, q) are the diagnostic tests of the models. Before applying the GARCH model, it is important first to check for conditional heteroscedasticity, which is also known as ARCH-effects. Such effects can be detected by checking the autocorrelation in the mean-centered squared residuals, which are received from ordinary least squares (OLS) regression (Ruppert, Matteson, 2015, p.355). Let the residuals of the mean equation take the form $a_t = r_t - \mu_t$. There are two variants to check the squared residuals a_t^2, which are used to detect the ARCH-effects (Tsay, 2010, p.114-115):

1. Applying Ljung-Box statistics $Q^2(m)$ for the a_t^2 series. The null hypothesis states that the first *m* lags of the autocorrelation function of a_t^2 series are zero.

   H_o: $p(1) = 0, p(2) = 0, \ldots, p(m) = 0$. (no ARCH effects)
   H_1: $p(1) \neq 0, p(2) \neq 0, \ldots, p(m) \neq 0$. (series exhibits ARCH effects)
   The null hypothesis is rejected when p-value of F statistics is less than $\alpha = 0.05$.

2. Applying Lagrange Multiplier (LM) test, which is variation of the F-statistics for the centered R^2 of the regression for $a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 + e_t$ (Tsay, 2010, p.114-115).

   H_o: $\alpha = 0$ in the linear regression (no ARCH effects)
   H_1: $\alpha \neq 0$ (series exhibits ARCH effects)

The results of both heteroscedasticity tests are presented in the Table 8.

	Ljung-Box for Q^2 Test		Lagrange Multiplier Test	
	$Q^2 stat$	*p-value*	*LM*	*p-value*
IBrX	722.69	2.2e-16	257.25	2.2e-16
IMOEX	344.28	2.2e-16	160.79	2.2e-16
NIFTY 500	220.98	2.2e-16	143.29	2.2e-16
Shenzhen Component	35.796	9.123e-05	28.498	0.00457
FTSE/JSE Africa all share	581.03	2.2e-16	223.51	2.2e-16

Table 8: Heteroscedasticity tests

Table 8 contains p-values of the Ljung-Box test for ARCH (m), where m = 10 and of the LM test for ARCH (m), where m = 12. The results with a statistically significance at the 5% level reject the null hypothesis that residuals are not correlated (p-values are less than 0.05). Therefore, ARCH-effects were confirmed in time series up to 10 and up to 12 respectively. As a conclusion for the detection of the conditional heteroscedasticity, an appropriate ARCH model should be estimated for the better results.

7.6. Variables correlation

To avoid the multicollinearity problem, which leads to reduced precision of the estimated coefficients and weakens the statistical power of regression models, it is important to first check the correlation of the explanatory variables. The tables below present the correlation matrixes between stock indices and independent variables for each country within observed period January 1st, 2020, to December 31st, 2021.

Parameters (Brazil)	(LN) IBrX	(GR) cum. CC	(GR) cum. MC	(GR) EPU	(LN) GRI
(LN) IBrX	1.000				
(GR) cum. CC	-0.107	1.000			
(GR) cum. MC	-0.266	0.428	1.000		
(GR) EPU	0.042	0.092	0.057	1.000	
(LN) GRI	0.080	-0.084	0.029	-0.039	1.000

Table 9: Correlation matrix for Brazil

Table 9 shows, both Covid-proxies have weak negative correlation with stock index and both, growth rate of EPU index and GRI, are slightly positive correlated.

Parameters (Russia)	(LN) IMOEX	(GR) cum. CC	(GR) cum. MC	(GR) EPU	(LN) GRI
(LN) IMOEX	1.000				
(GR) cum. CC	-0.063	1.000			
(GR) cum. MC	0.040	0.347	1.000		
(GR) EPU	0.030	-0.015	-0.016	1.000	
(LN) GRI	0.056	-0.003	0.100	-0.052	1.000

Table 10: Correlation matrix for Russia

In Russia (Table 10), only a weak negative correlation between growth rate of cumulated reported cases with stock index can be observed. The other variables are positively correlated with the stock market.

Parameters (India)	(LN) NIFTY 500	(GR) cum. CC	(GR) cum. MC	(GR) EPU	(LN) GRI
(LN) NIFTY 500	1.000				
(GR) cum. CC	-0.054	1.000			
(GR) cum. MC	-0.061	0.284	1.000		
(GR) EPU	-0.023	0.029	0.000	1.000	
(LN) GRI	0.053	-0.066	0.082	0.019	1.000

Table 11: Correlation matrix for India

The correlation matrix of India (Table 11) shows the most expected results, namely the negative correlation of COVID proxies with stock index and positive correlation between government response and market performance.

Parameters (China)	(LN) SZI	(GR) cum. CC	(GR) cum. MC	(GR) EPU	(LN) GRI
(LN) SZI	1.000				
(GR) cum. CC	0.025	1.000			
(GR) cum. MC	-0.037	0.277	1.000		
(GR) EPU	0.077	-0.005	-0.010	1.000	
(LN) GRI	-0.019	-0.323	-0.332	0.039	1.000

Table 12: Correlation matrix for China

The correlation results of Chinese regressors give disconcerting output (Table 12), showing - against the odds - positive correlation between EPU index and stock and negative correlation between GRI and stock index. New COVID-19 cases and new mortality cases show weakly positive and negative correlation respectively.

Parameters (South Africa)	(LN) JALSH	(GR) cum. CC	(GR) cum. MC	(GR) EPU	(LN) GRI
(LN) JALSH	1.000				
(GR) cum. CC	-0.186	1.000			
(GR) cum. MC	-0.030	0.090	1.000		
(GR) EPU	0.023	0.03	-0.008	1.000	
(LN) GRI	0.084	-0.019	0.092	-0.074	1.000

Table 13: Correlation matrix for South Africa

Note: The correlation of variables with EPU Index for South Africa was estimated over the period of 01.01.20-30.11.21, when the data for EPU index was available.

As a result, for South Africa shown in Table 13, both COVID proxies perform negative correlation process with the stock index and there is a weak positive correlation between stock index and both indices.

As most of the COVID proxies and other independent variables are correlated with each other on different levels, it was decided to separately add explanatory variables in each model to achieve trustworthy results.

7.7. Model parameters selection

After the conditional heteroscedasticity in residuals was confirmed, the next step requires to specify the model and, especially to find the most suitable order specification for each model component. Two approaches are typically used for the order specification of the model. The first approach is to use autocorrelation functions and the second approach applies informational criteria (Tsay, 2010, p.46).

Autocorrelation Function (ACF), which is presented as p(h) = corr(r_t, r_{t-1}) is used to estimate the MA(q) order. The summary correlation of errors is usually visualized in a correlogram and shows the correlation coefficients of the lagged series.

Partial Autocorrelation Function (PACF) is a function of ACF and is used to determine the AR (p) order. The function shows the correlation between two variables considering the information about the correlation between response variable and preceding predictor variable. Thus, for instance, the laf-3 PACF shows the correlation between r_t and r_{t-3} over an AR(2) model (Tsay, 2010, p.47). Along with ACF correlogram, a graphical visualization is used for PACF. In practice, it has proven to be difficult to interpret the correlograms because of the large observations and frequency of time series. Because of that reason more appropriate information criteria are widely used to choose the best set of parameters for the model.

Both Akaike Information Criterion (AIC) and Schwarz–Bayesian information criterion (BIC) are log-likelihood based. In this study, the AIC criteria, as the widely used technique, was chosen for parameters estimation. AIC criteria can be defined as (Tsay, s2010, p.48):

$$AIC(\ell) = \ln(\sigma_\ell^2) + \frac{2\ell}{T}$$

Equation 10: Akaike Information Criterion equation

where σ_ℓ^2 is the maximum-likelihood estimate of σ_a^2, which the variance of a_t

T is number of observations.

The criteria work the rule that the smaller value of criteria result is preferable since small values tend to maximize likelihood and minimize lag ℓ, which measures model complexity. The parameters will be selected for each regression with a certain exogenous variable. And as it was already mentioned, GARCH (1,1) model is proved to perform reliable output, so it will be used in the regressions for the modeling volatility.

	Brazil	**Russia**	**India**	**China**	**South Africa**
GR. cum. new cases	ARMA (1,1)	ARMA (2,2)	ARMA (2,3)	ARMA (3,2)	ARMA (3,2)
GR. cum. mortality cases	ARMA (2,2)	ARMA (1,1)	ARMA (3,3)	ARMA (3,2)	ARMA (2,2)
GR. EPU	ARMA (2,2)	ARMA (3,3)	ARMA (2,3)	ARMA (2,2)	ARMA (1,1)
LN GRI	ARMA (2,2)	ARMA (3,3)	ARMA (3,3)	ARMA (2,2)	ARMA (2,3)

Table 14: Selected parameters for ARMA models

Table 14 presents the best selected parameters for ARMA (p,q) part, based on the AIC test results, which were run in R software.

7.8. Estimation Results

The Statistical Packages "rugarch" and "sGARCH" functions were used to develop the time-series database and estimate the parameters of the models in the objective-oriented software R. Explanatory variables as the external regressors were included in both mean and volatility equation. Table 15 presents the main findings for coefficients of the explanatory variables, which are of special interest. The whole performance of all parameters is shown in Appendix Table A- 1 to Table A- 5.

	Brazil	Russia	India	China	South Africa
			GR cum. NC		
mean equation	-1.207 (1.640)	-1.070 (0.928)	-0.308*** (0.000)	0.105 (0.208)	-2.629*** (0.000)
volatility equation	0.000 (1.133)	3.641** (1.598)	2.909*** (0.237)	0.530** (0.255)	5,407** (2.373)
			GR cum. MC		
mean equation	-0.456 (1.202)	0.129 (1.056)	-3.934*** (0.001)	-0.134 (0.585)	0.276 (0.209)
volatility equation	0.000 (3.692)	0.000 (1.231)	0.535 (0.999)	1.068** (0.475)	0.407 (0.996)
			GR EPU		
mean equation	0.568 (0.457)	0.747 (0.456)	-0.758*** (0.001)	0.980 (0.948)	-1.013 (1.995)
volatility equation	0.000 (1.011)	0.000 (0.547)	0.394 (0.395)	0.000 (1.041)	0.000 (3.048)
			LN GRI		
mean equation	0.098 (0.076)	0.033 (0.054)	0.033 (0.042)	-0.199*** (0.000)	0.040*** (0.012)
volatility equation	0.000 (0.022)	0.000 (0.010)	0.000 (0.014)	0.000 (0.034)	0.000 (0.009)

Table 15: Estimation results for ARMA-GARCH models for the 01.01.20-31.12.21

*Note: The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations.*

7.9. Check of the adequacy of the fitted models

To check the adequacy of the chosen models, several misspecification tests were computed. In this case, to check the adequacy of the fitted GARCH model, the Ljung-Box test can be used. Therefore, to check the ARCH effects, Ljung-Box test of standardized residual and ARCH-LM test was made. Also, to test the autocorrelation, Ljung-Box test of standardized squared residuals was applied. The null hypothesis of these tests state, that there is no autocorrelation among the residuals. The model considered as adequate, when the residuals are not correlated and consequently have no significant autoregressive conditional heteroscedasticity (Akintunde, et al, 2013).

	Q-Stat (p-value)	ARCH-LM (p-value)	Q^2-Stat (p-value)
Brazil			
ARMA(1,1)-GARCH(1,1) for GR cum.CC	0.972	0.139	0.967
ARMA(2,2)-GARCH(1,1) for GR cum.MC	0.375	0.336	0.697
ARMA(2,2)-GARCH(1,1) for GR EPU	0.395	0.404	0.713
ARMA(2,2)-GARCH(1,1) LN GRI	0.320	0.295	0.677
Russia			
ARMA(2,2)-GARCH(1,1) for GR cum.CC	0.913	0.919	0.1305
ARMA(1,1)-GARCH(1,1) for GR cum.MC	0.618	0.788	0.12722
ARMA(3,3)-GARCH(1,1) for GR EPU	0.565	0.504	0.30501
ARMA(3,3)-GARCH(1,1) LN GRI	0.606	0.825	0.14262
India			
ARMA(2,3)-GARCH(1,1) for GR cum.CC	0.7563	0.619	0.4729
ARMA(3,3)-GARCH(1,1) for GR cum.MC	0.0626	0.867	0.2479
ARMA(2,3)-GARCH(1,1) for GR EPU	0.335	0.240	0.2704
ARMA(3,3)-GARCH(1,1) LN GRI	0.0479	0.192	0.1974
China			
ARMA(3,2)-GARCH(1,1) for GR cum.CC	0.574	0.801	0.7894
ARMA(3,2)-GARCH(1,1) for GR cum.MC	0.432	0.888	0.7247
ARMA(2,2)-GARCH(1,1) for GR EPU	0.956	0.995	0.7984
ARMA(2,2)-GARCH(1,1) LN GRI	0.518	0.904	0.6543
South Africa			
ARMA(3,2)-GARCH(1,1) for GR cum.CC	0.862	0.870	0.881
ARMA(2,2)-GARCH(1,1) for GR cum.MC	0.738	0.030	0.325
ARMA(1,1)-GARCH(1,1) for GR EPU	0.897	0.057	0.312
ARMA(2,3)-GARCH(1,1) LN GRI	0.719	0.070	0.3670

Table 16: Diagnosis test's results for the fitted models

Notes: Q-Stat. is the empirical statistics of the Ljung–Box test and Q^2-Stat symbolizes the Ljung–Box statistics of the squared residuals. Both tests results are presented on the lag(1) and ARCH-LM test on the lag(3), and therefore the results are representative. The full results for all lags are presented in Appendix Table A- 6 to Table A- 10

Table 16 shows the diagnosis tests' results for each estimated and fitted model. The p-value at the given lags in all models are greater than 0.05. Therefore, the insignificance of p-value doesn't allow to reject the null hypothesis and hence proves that GARCH model can capture heteroscedasticity and therefore adequately fitted the data. An exception is only in the model for growth rate of cumulated mortality cases in South Africa, where the p-value is less than 0.05, but still the significance is present on 1% level.

8. Data Interpretation and Results

COVID new reported cases

The estimation results of the ARMA-GARCH models including the exogenous variable in mean equation show the negative impact of the COVID new reported cases on stock indices return in all BRICS countries, except of China. Moreover, the negative impact is shown to be statistically significant on 1% level in India and South Africa. The explanation of such high significance can be the fact, that India and South Africa were countries with high number of daily new cases. India (1'380 Mio population) reached 414'188 new cases a day on May 6th, which would be calculated as 297.25 cases per one million inhabitants. South Africa with its least population (59 Mio), reached up to 37'875 new cases a day, which would calculate to a ratio of 630.81 cases per day in relation to their population, which was the highest ratio reached in BRICS countries in the period analyzed in this study (Source: ourworldindata.org). Of course, such information would influence the investor sentiment and stock market reaction. Unlike other BRICS countries, the impact of new COVID-19 cases on stock market of China shows the positive insignificant effect, which is out of the expectation and suggest, that there is no relation between daily new reported cases and stock performance. Such result can be explained firstly with the strong containment measures, which were immediately introduced, compared to the small amount of new reported cases (compared to China's population). At that stage of the virus development investors were reacting to the announcements of the government and the WHO rather than to the COVID-19 infection numbers themselves. Secondly, as mentioned earlier, stock markets are often closely related to each other. When COVID-19 started in China, stock markets in the rest of the World remained calm and did not negatively impact Chinese stocks. When the virus started to hit the rest of the World, other financial markets were not only more sensitive to COVID-19 infections numbers, but also negatively impacted each other. At that time the Chinese financial market had already started to recover. But these findings don't exclude a possible significant negative effect, taking a closer look at a shorter time period during the early days of outbreak, what leaves an opened field for future investigations.

The effect of the covariate in the volatility equation is significantly positive over all countries, other than Brazil. The effect points out, that the growth rate of new reported cases increases the magnitude and therefore increases the volatility of stock markets. Among the observed countries South Africa has the largest constant coefficient (0.23) and coefficient of exogenous variables (5.407) in volatility equation. This points to important findings, the COVID-19 crisis shock had the strongest significant impact on South African stock market, bringing turbulence in stock returns. The least market volatility was detected in China with the mean coefficient of 0.051. The alpha component ε , which measures the reaction to conditional volatility is relatively large (above 0.1) in South African and Brazilian market, means that volatility is very sensitive to market events. The high coefficient of beta β component (above 0.9) was found only in China and implies that volatility takes a long time to die out following a crisis.

In that regard the null hypothesis is rejected for two countries, India and South Africa, and the alternative hypothesis is accepted: the number of new reported cases has a predictable power on stock market. For the rest of the countries the null hypothesis remains valid.

COVID mortality cases

The estimated coefficients of the COVID-19 mortality cases in mean equation reveal in general negative insignificant impact on stock returns. Though the high significance at 1% with the high estimated coefficient of covariate is observed only in India and is explained with the highest number of mortality cases among the BRICS countries. In this context two countries, Russia and South Africa, stand out with positive insignificant impact of mortality cases on stock return.

Looking at the results of volatility equation, South Africa is again on the first place with constant parameter ω (0.134) determining the highest long term average volatility. The lowest constant volatility show Russia, India and China. However, exogenous regression in equation reveals that among all countries the highest significant impact at 5% level on volatility is observed in Chinese market. That means that with the growing numbers of official mortality cases, the volatility also increases.

In that regard the null hypothesis for all BRICS countries, except of India, cannot be rejected, which means that the stock markets do not significantly relate to the number of new mortality cases.

Economy Policy Uncertainty

Surprisingly enough, but results reveal, that only two countries, in particular India and South Africa, show negative impact of the increased economic uncertainty on their stock markets. Even though the negative impact of EPU index in South Africa has the biggest coefficient (-1.013), it is still insignificant. However, the increased EPU Index has a significant negative impact at 1% level on return of Indian stock index.

That fact has also reflection in the influence on the exogenous variable on the volatility of Indian stock index, where the growth of EPU index at 1% leads to increase of volatility by 0.394. The coefficient of the mean volatility ω is shown to be the largest (0.135) in South Africa. The results of other observed countries don't show any significant impact of the increased uncertainty, caused by the COVID outbreak. Since the initial data of EPU index was collected on monthly basis and each monthly value was then spread to each day of the respective month, any relation of volatility within one month period would not be reflected and results might therefore be misleading.

Still, based on the findings of this methodology, the null hypothesis is accepted for all BRICS countries, except of India, and states, that economic policy uncertainty doesn't have a significant impact on the stock market.

Government Response

The obtained result with included covariate of GRI Index reveals, that government response positively affected all countries, except of China. The high significant impact at 1% confidence level was revealed in China and South Africa. However, the coefficients of these two countries are preceded by opposite signs and point to different relation to the variable. Therefore, an increase of the index in 1% leads to increase of the stock return mean by 4% in South Africa and leads to decrease of stock return by 20% in China. Other countries have showed insignificant impact.

Investigating the impact of the variable on the stock market's volatility, we can see that none of the countries indicate any significance, showing all the coefficients of the exogenous variables by zero. By contrast the coefficient of the unconditional variance ω reveal, that the more vulnerable market is in South Africa.

Based on the results, the null hypothesis is rejected for South Africa and China, and therefore the alternative hypothesis is accepted and claims, that government response has a predictable power on these stock markets.

9. Industry Analysis

9.1. Data preparation and estimation results

The shock, which was brought by Coronavirus pandemic, struck world economy. Lockdowns and a slump in consumer spending led to a labour market implosion that saw millions of full-time jobs disappearing almost overnight (The Economist, 2020a). The pandemic undeniably had many losers but as the first shock from the initial outbreak in the first quarter 2020 began to abate, clear winners began to emerge (The Economist, 2020b). Such after-effects became object of interest for many researchers and market participants in investigating the industries' performance during the COVID-19 outbreak. As such, Abay et al. (2020) used historical and near real-time data from Google Trends to determine the impacts COVID-19 had on selected sectors of economies across 182 countries. They quantified the impact of the pandemic on two groups of interactions: first, services, that require face-to-face interactions (retail trade, hotels, restaurants) and secondly, services, that can be performed remotely (like information and communication technology). Their findings reveal that demand in the first group has substantially contracted and demand for the second group of services had increased significantly. More specifically, countries with at least ten confirmed cases could experience a reduction of services in the first category of up to 79%, while enjoying a comparable increase of services in the second category.

Another study looked at the effects the COVID-19 crisis on specific industries (Ramelli et al., 2020). The results indicated that *Telecom* and *Pharma* industries performed relatively well, but food and staples retailing performed negatively, especially in the incubation and fever period. *Energy, Consumer Services*, and *Real Estate* also suffered particularly. As the world went into lockdown from COVID-19, the demand for oil sunk at an unprecedented rate. So, the negative impact on energy sector was even intensified by the oil price shock, which occurred in the fever period.

However, categorizing industries in their entirety as winners or losers should be exercised with caution because it ignores the firm's individual characteristics, which contribute greatly to its ability to survive and even getting prosperous in the face of macroeconomic hardships. Economic downturns serve as a sorting mechanism: firms with leveraged balance sheets and weak business models quickly stumble. Healthier firms will likely endure, and some may even succeed, depending on their ability to adapt (The Economist, 2020c). A firm's resilience is not limited to its financial character as noted above; its market capitalization can also play a vital role.

The regression results obtained in the previous section, identified South Africa as the country with the highest significant negative impact of COVID-19 proxies, confirming a strong relation between new cases and stock market returns. The development of new infection cases in South Africa in daily new cases as shown in Figure 2 as well as the related graph of cumulated cases per one million of population in Figure 1 clearly reflect different waves of infection spreads in a distinct pattern. From this perspective South Africa was chosen as the most interesting option for further industry-level analysis. The analysis is aimed to investigate the impact of the growth rate of daily cumulated new cases on the stock market of each industry of the FTSE/JSE Africa all share stock index. Additionally, as South Africa also showed an impact at 1% significance level in the regression for GRI, this variable was also added to the industry analysis to understand how new cases of infections and government response impacted different areas of the South African industries.

The eleven sectors listed by the Global Industry Classification Standard in Bloomberg include *Materials, Consumer Discretionary, Consumer Staples, Industrials, Real Estate, Energy, Financials, Utilities, Health Care, Information Technology, Communication Services* (Bloomberg.net). The indices for each sector were calculated manually using the capitalization-weighted method[2].

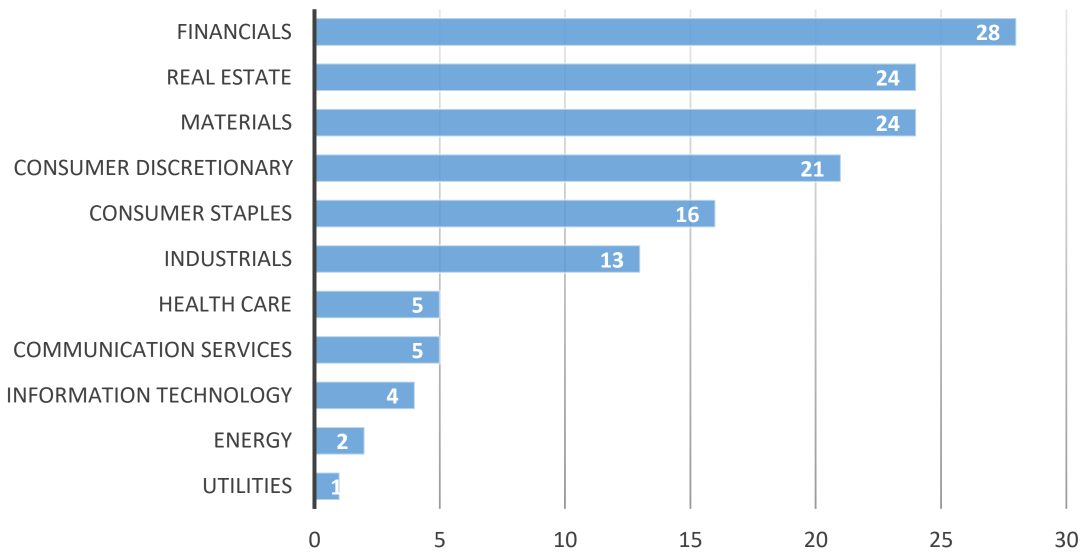


Figure 8: Bar Chart of Sectors of JALSH Index

[2] *Capitalization-weighted Index* is a capital market index in which the constituent securities are weighted based on their market capitalization, which equals the product of its price per share and total number of common shares outstanding. The weight of each security is calculated by the ratio of its market capitalization to the sum of market capitalization of all constituent securities.

Figure 8: *Bar Chart of Sectors of JALSH Index* shows the eleven sectors, in which all the firms within the sample were categorized as per December 31, 2021. The industry *Financials* containes the greatest number of firms, the sector *Utilities* only one. Since the only firm in sector *Utilities* started to trade on the stock market only in January 2021, it was decided to exclude it out of the analysis, as its performance is not representative. Therefore, 142 companies of the index grouped in 10 industries were included for the cross-industry analysis.

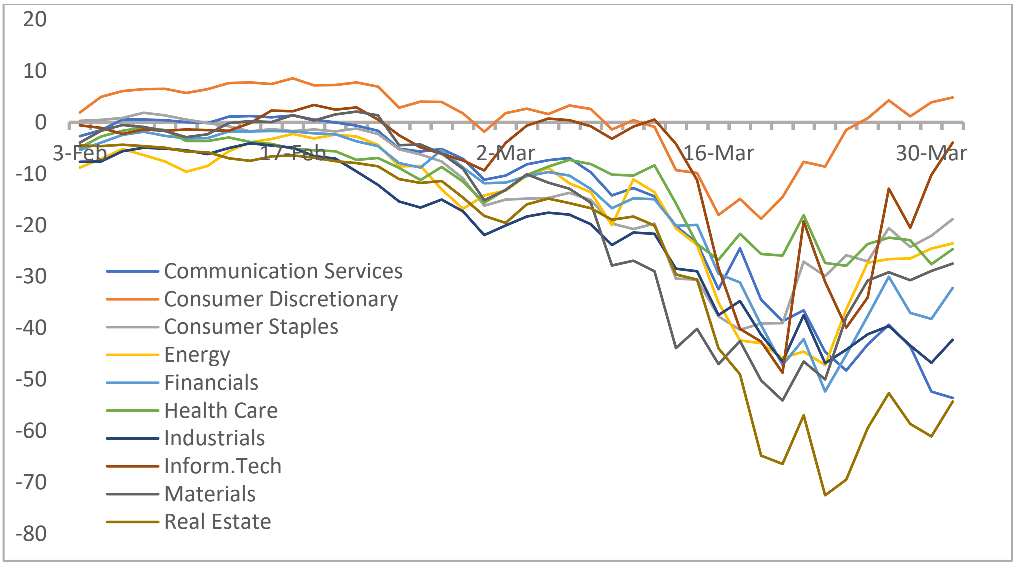


Figure 9: Line Chart of Cumulated returns by industry sector during the period 01.02.2020-31.03.2020

Figure 9 graphs the cumulated returns by sector over two months February and March 2020, when the "fever" period took place. As expected, based on the significance of the COVID-19 impact in South Africa, all industry sectors were affected and showed decline. Still, the graph also depicts, that *Consumer Discretionary, Information Technology* and *Health Care* are shown as less effected by the crisis, while the sector *Real Estate and Materials* incur heavy losses. Considering, that South Africa was showing the strongest impact of trade, as noted earlier, and a possible stronger relation of these industries to foreign investments and global trade, the depicted declines could be explained. At the same time, the government in South Africa announced its first response end of March, the markets show a certain recovery, with the strongest reaction in *Consumer Discretionary* and *Information Technology*. The results, obtained by applying ARMA-

GARCH model, will give more understanding about the relation of COVID-19 and government response across the entire research time frame of 2020 and 2021.

Sector	GR of cum.CC		LN GRI	
	Mean equation	Volatility equation	Mean equation	Volatility equation
	ARMA(2,2)-GARCH(1,1)		ARMA(2,2)-GARCH(1,1)	
Communication Services	-3.104** (1.450)	6.697** (2.823)	0.070 (0.079)	0.006 (0.027)
	ARMA(3,3)-GARCH(1,1)		ARMA(1,2)-GARCH(1,1)	
Consumer Discretionary	0.837*** (0.000)	3.936** (1.862)	-0.029*** (0.000)	0.000 (0.041)
	ARMA(2,2)-GARCH(1,1)		ARMA(2,2)-GARCH(1,1)	
Consumer Staples	-0.751 (1.052)	10.485** (4.229)	0.032 (0.040)	0.020 (0.022)
	ARMA(1,3)-GARCH(1,1)		ARMA(1,1)-GARCH(1,1)	
Energy	-3.299*** (0.000)	15.619* (9.030)	0.514* (0.266)	0.000 (0.109)
	ARMA(3,3)-GARCH(1,1)		ARMA(2,1)-GARCH(1,1)	
Financials	-2.896*** (0.001)	2.208* (1.331)	0.068*** (0.020)	0.000 (0.018)
	ARMA(2,2)-GARCH(1,1)		ARMA(1,1)-GARCH(1,1)	
Health Care	-0.362 (1.373)	5.121* (2.778)	0.060*** (0.000)	0.061 (0.053)
	ARMA(3,2)-GARCH(1,1)		ARMA(3,3)-GARCH(1,1)	
Industrials	-2.058*** (0.519)	8.003** (3.653)	0.127*** (0.000)	0.000 (0.022)
	ARMA(1,1)-GARCH(1,1)		ARMA(1,2)-GARCH(1,1)	
Inform. Technology	1.381 (2.214)	70.767*** (21.494)	0.085*** (0.0000)	0.375*** (0.091)
	ARMA(3,2)-GARCH(1,1)		ARMA(3,2)-GARCH(1,1)	
Materials	-1.359*** (0.001)	28.817** (13.253)	0.053*** (0.020)	0.000 (0.025)
	ARMA(1,1)-GARCH(1,1)		ARMA(1,1)-GARCH(1,1)	
Real Estate	-1.696 (1.597)	4.926** (2.208)	0.089* (0.048)	0.000 (0.011)

Table 17: Estimation results of cross-sectors analysis of JFSE/JSE Africa all share index for the period 01.01.20-31.12.21

*Note: The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations.*

9.2. Data Interpretation and Results

COVID new reported cases

The estimation results of cross-industry analysis obtained with ARMA-GARCH Model with the included exogenous variable in mean equation indicate significance at 1% level negative impact of the growth rate of cumulated new reported cases in several sectors: *Energy, Financials, Industrials* and *Materials*. The negative significance at 5% level is revealed in *Communication Services* sector. This clearly implies, that COVID-19 new reported cases, have led to decrease of the stock market return in most of the sectors. The only sector, which has a positive significant on 1% level impact, is *Consumer Discretionary*. By other sectors it is indicated insignificant either negative (*Real Estate, Health Care, Consumer Staples*) or positive (*Information Technology*) impact. At the same time, the results of the regression analysis with the exogenous variable in volatility equation reveal the significant positive impact of new reported cases on market stock volatility across all sectors. It means, that the increase of the growth rate of cumulated new reported cases by one unit leads to increase of the stock market volatility. The highest significance at 1% level was observed in *Information Technology* sector and the lowest, at 10% level, in *Financials* and *Health Care* sectors. The highest estimated coefficients of constant volatility ω is observed in the sectors *Information Technology* (2.521) and *Energy* (1.643).

Government Response

The estimated coefficients of the logarithm of GRI in mean equation reveal positively impact in all sectors except of *Consumer Discretionary*, where negative and significant effect is indicated at 1% level. Five models fitted for *Financials, Health Care, Industrials* and *Information Technology* show statistically significant coefficients at 1% level, two sectors, *Energy* and *Real Estate* reveal positively significance at 10% level. In general, it can be concluded, that governmental interventions positively affect the stock market of all sectors and lead to stock return rise. The results also indicate, that GRI, as independent variable, plays a big role in predicting stock market performance. After including the logarithm of GRI in the volatility equation, the coefficient of the exogenous variable (0.375) shows a significance at 1% positive impact on *Information Technology* sector, which means that changes in GRI caused high fluctuation of return in the sector, therefore increased its volatility. Also, the results show, that all other sectors have insignificant impact of the governmental interventions on stock market volatility. The highest estimated coefficients of constant volatility ω are observed in the sectors *Health Care* (0.246) and *Materials (0.235).*

The results are partly consistent with the findings of Szczygielski et al. (2022), who have found that industries, which are most impacted by COVID-19 uncertainty, are the energy related industries, and the least impacted are food, staples retailing and telecommunication industries. The differences in results reveal, that the impact of the COVID-19 crisis on industries globally, still can differ when examined within a specific country.

10.Summary and Implications

The prime goal of this paper was to examine the effects of COVID-19 proxies, such as growth rate of cumulated new reported cases and growth rate of cumulated mortality cases, on the stock market return and volatility persistence of the BRICS countries. In addition, the effect of government response index as well as the economic policy uncertainty index on the stock market performance was analyzed. The impact of the defined exogenous variables was examined using ARMA-GARCH model adding the explanatory variables both to the mean and volatility equation. Based on information criteria the optimal model parameters were chosen for each regression.

The primary variable of interest was the estimated coefficient of growth rate of the cumulated new reported COVID-19 cases, which aimed to analyze the impact of COVID-19 crises. The findings revealed that there were important differences in how investors' risk perceptions changed upon announcements of COVID-19 indicators and response measures. The results show that the coefficient was negative for four out of five BRICS countries and significant for two countries. Based on the negative sign and p-value less than 0.05, the null hypothesis for non-impact of the coronavirus was rejected for India and South Africa. In contrast, the significance in volatility equation was found for four countries out of five with a positive preceded sign in coefficients. These results point to the high impact of the COVID-19 outbreak on the stock market volatility. The results of the model with included growth rate of mortality cases as an explanatory variable suggesting, that India and China were affected by growing number of mortality cases. Notably, that the growth rate of cumulated mortality cases impacted the stock market of these two countries differently, increasing the stock volatility in China and decreasing the stock return in India.

Comparing these two variables, it may be concluded, that the news about new reported cases have influenced the investors sentiment more and therefore had more impact on stock market volatility, rather than the information about new mortality cases. It is worth to mention, that the countries showing the highest significance of the COVID-19 impact, India and South Africa, were also the countries, which showed the highest daily new reported cases (India) and the highest number of daily new cases per million inhabitants (South Africa) compared to other BRICS countries at a specific point of time. These two countries already entered the pandemic with an economic slowdown and have showed the highest decrease in GDP growth rate in the first quarter 2020. In the same year, India and South Africa were distinctive for the biggest contractions both in export and import. COVID-19 related closures of cities and ports in China caused production shutdowns and supply chain issues in India and South Africa, which impacted their economies. In addition, South Africa was known as a large materials and commodities supplier and therefore also felt the decline of demand in China. Within the first quarter 2020 the economic activity in India fell in two times, which caused a sharp rise of unemployment from 6.7% in March 2020 to 26% in April 2020 and reduce of consumer activity. These factors might have had an influence on the economies and stock markets at the same time as the increasing COVID-19 cases, which might have emphasized the calculated effect. As a generalized finding, it might be possible to say, that financial markets might show a relation to COVID-19 proxies only in extreme circumstances.

As a reaction to the COVID-19 outbreak the economic policy uncertainty was the next object of interest of the analysis. Surprisingly, the estimation results have found the evidence of the significant negative impact of the EPU index at 1% level only in India, a country, as it has been already noticed, with a weak health and volatile economic system. Negative insignificant impact was also indicated in South Africa. The p-values of the coefficients of other countries both in mean and volatility equation are greater than 0.05. Therefore, it could be recommended that foreign investors hedge against economic policy uncertainties by investing in Brazilian, Russian, or Chinese stock markets. Generalized, it may be concluded, that economic policy uncertainty doesn't have a significant impact on stock markets and doesn't affect the volatility of a stock market. It must still be considered that the measure of EPU index with its monthly frequency might have led to unreliable results. For future studies, it would be recommended to apply a different representative index for uncertainty on a daily basis.

Examining the impact of the governmental response to the COVID outbreak, the results of the fitted models have revealed, that the index has a predictable power in China and South Africa. But the preceded signs of the estimated coefficients are different, which means that the impact was negative in China and positive in South Africa. Regarding the GRI as an explanatory variable in volatility equation has no predictable power over all BRICS countries' stock market. Such a contrast in the findings can be explained firstly with a different approach of government to contain the virus and minimize the negative consequences and secondly with the timing, respective sequence a country entered the pandemic. As such, China was the first country and therefore not effected by economic reactions of other markets to the same extend as other markets would be later. China's economy still had the benefit of the doubt, which kept the international attention of investors still low. When the magnitude became more visible, China became famous for its "draconian measures", which consisted in zero-Covid policy. Though the Chinese containment strategy, as it later emerged, had shown its high effectiveness and "bought the world time to essentially prepare better" (Begley, 2020), there were those, who found the strategy overreacted. The aggressive measures caused a panic in the country and scared investors to search for alternative investments. Therefore, the drastic government response in China negatively impacted the stock market. The situation in South Africa was different. The country was already in recession in the beginning of the pandemic, the regulatory and legislative system was not stable. the corruption level was high, and the investors' confidence is low. So, the announced lockdowns were destructive for many economic and social fields. At the same time, South Africa entered the pandemic late compared to other BRICS markets and was able to respond with appropriate and effective measures in a fast and coordinated approach. This was even recognized by the WHO. It can be suggested that investors were prepared for such measure implementations, which caused a positive impact. The general conclusion based on results for the most countries, GRI did not show a significant impact on BRICS economies or its volatilities. This would still be an interesting field for further studies to understand, if the growing understanding of a pandemic and introduced measures and the sequence of a country entering a pandemic could lead to predictable power.

As an extension of the study, an industry analysis of the South African stock markets was done to reveal industries with the biggest impact of the growing number of COVID cases and the impact of the governmental interventions. The results of the analysis have shown that all the sectors, except of Consumer Discretionary, experienced a negative impact on stock markets performance. But the biggest impact was detected on stock market volatility. As so, growth rate of new reported cases significantly increased volatility across all sectors. The impact of the government response index was mostly positive. Only one sector Consumer Discretionary has shown the negative significant impact. Such findings suggest that government response concluded more positive news, which stem from announced economic policies, than negative news. Overall, the results for the industries are in line with the overall expectations based on the BRICS countries' outcome.

To gain a better understanding of the obtained results, it is worth to also review other papers, which have used the COVID-19 stock market crisis to test the stock resilience of BRICS countries. The results of the studies, which were aimed to investigate the impact of the COVID-19 crisis, varies from author to author by the examined period, employed statistical models and approaches. Still, the findings of this paper are in line with the findings of Ledwani et al. (2021), who found a negative effect of COVID-19 across all BRICS countries except of China. Bakry et al. (2021) employed the GJR-GARCH model to investigate how the daily COVID-19 announcements and government stringency responses relate to the volatility of stock market indices in emerging and developed markets. Their research has found evidence, that emerging markets react stronger to COVID-19 crisis. Using the sub-indices of Stringency Index as independent variable, the researchers revealed differences in how volatility of emerging market responds to changes of certain sub-indices. Thus, there is a positive and significant relationship between volatility and COVID-19 infection and mortality cases, which was confirmed in this study. There are a lot of research papers investigating the spillover effects of EPU, the global impact of EPU in pre-pandemic time. However, there is a lack of studies, which examined the impact with the same measures of economic uncertainty on stock market of BRICS countries during the COVID pandemic. Therefore, there is no relevant comparison with the results of other researchers. But another interesting finding, which is worth some attention, was found in the research of Scherf et al. (2022). The authors investigate how stock markets of OECD and BRICS countries reacted to the news of national lockdown restrictions. The effect was in general negative, but it was found, that the markets positively reacted to later relaxations of restrictions.

Never-the-less, the current study has some limitations. Firstly, it has used the data over two years and has examined a long-term effect of the independent variables, such as COVID-19 proxies, EPU index and GRI, which turned to be insignificant in majority of observed countries. This can be explained with a “short memory” of the ARMA process in the financial time series when the shock doesn’t affect the behavior of the analyzed series in a long run. It would be interesting to examine the predictable power of already used explanatory variables during shorter periods, which may also be different for each country. Secondly, as already mentioned, the time series of EPU index was provided only on a monthly base and then manually transformed into daily data, which could influence the robustness of the results. Thirdly, as it was already mentioned government response index contains different indicators, which represent different dimensions of policies, such as containment and closure policies, economic and health policies. Since the reaction on the announced policies could be quite opposite (negative to closure and positive to economic support measures), the results may be misleading. Future research examining each group of indicators separately would be an interesting supplement to this study. Fourthly, within the industry analysis it was decided to use JALSH index, which consists of 142 constituents. Considering the small sample size of companies and the grouping into 11 sectors, some of the sectors included less than five companies. The results were therefore more indicative, but not representative for those industry sectors as if the index would comprise analysis of a wider range of industries (e.g. 68 industries following MSCI's Global Industry Classification Standard) with about 500 securities or a variety of indices. An. The described limitations don't compromise the results of the current research findings, rather show additional opportunities for the future investigation of health crisis impacts.

Finally, one of the most important components of each study is the employment of a proper model. The ARMA-GARCH model was chosen to account for volatility of the stock market. The estimated results show that the value of parameters beta β (the value of variance coefficient) in all the models were close to one, which points to the volatility persistence. Moreover, the results of LM-test have shown, that ARCH-effects in the fitted models are absent and the results of Ljung-Box proved that residuals are not correlated. It can be concluded, that the ARMA-GARCH has coped with the task to capture the autocorrelation in returns and squared returns and also to model the conditional heteroscedasticity.

The ARMA-GARCH model is one of the successful and main models for volatility of financial instruments, what was confirmed in the current research. The initial results indicate that the model performs well on high-volatility stocks. As such, the model finds its wide application in finance. The model doesn't predict the future values of assets but describes the behavior of conditional variance. As so, it can be implied in risk management sphere, as for portfolio managers it's important to know what kind of exposure their assets incur. Bank and financial institutions use the model to measure the risk faced by their portfolios when they apply the concept "value at risk"[3] (VaR). The model can be also used by traders in real-life scenarios by applying short-long strategy[4]

[3] The estimate of amount, that will not exceed the expected losses for investments over a given period of time with a given probability.

[4] An investment strategy, that implies buying an asset when its value is expected to increase and selling short asset when its value is expected to decrease.

and bound strategy[5]. Still the model had some weaknesses. One of them was, that in GARCH models the positive and negative shocks have the same effect on conditional variation ("leverage effect"). Hence, as an extension of the current model a range of nonlinear asymmetric models (e.g. EGARCH, GJR-GARCH) were developed. For future analysis of financial time series in new fields of investigations, it could be beneficial to test and compare different autoregressive models.

The findings of this research might provide implications for international portfolio managers, investors, and government agencies. Due to attractive characteristics of emerging markets, such as low correlation with global market and potential growth in market capitalization, investors can allocate their investments in any of BRICS countries. However, they must carefully evaluate volatility of these markets and consider country and sector diversification. The study has also shed a light on the time series properties, so that market participants and regulators can be warned about accurateness of choosing a proper econometric model to test the persistent nature of data. The findings suggest that investors must consider countries' corruption level, governmental intervention measures as well as long- and short-term policies. It is recommended to improve institutional quality of governance in emerging markets, to adopt extensive policy measures to mitigate the adverse impact of occurring shocks and to boost the market.

Overall, the findings contribute to the existing literature on the impact of COVID-19 outbreak and stock market persistence. The results highlighted that stock market can be affected not only by internal financial factors, but also exogenous shock, such as the pandemic.

Although the COVID-19 pandemic is not rageful anymore and most restrictions in most countries were removed, still new variations of the virus occur and new waves of infections are reported, like in China in spring 2022. On February 24th, 2022, Russia engaged its military on Ukrainian grounds, which caused various sanctions mostly

[5] An investment strategy, that aims only to trade by market shocks (buying the bottom and selling the top within the set range).

imposed by the EU and the US with widespread impact on global economies, financial markets, inflation and even world food supply. This next historic event with global impact, overlapping with the outrunning effects of the previous event, underlines the value of the estimation of uncertainty and developing mitigation strategies. Herein this study will provide its contribution.

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Appendix

Parameters	GR cum.CC	GR cum.MC	GR EPU	LN GRI
Conditional mean equation				
μ	0.043	0.029	0.022	-0.350
	(0.059)	(0.058)	(0.059)	(0.297)
φ_1	-0.243	0.177 **	0.180 ***	0.177***
	(0.274)	(0.058)	(0.058)	(0.057)
φ_2		-0.814***	-0.816***	-0.815 ***
		(0.092)	(0.097)	(0.093)
φ_3				
θ_1	0.097	-0.280 ***	-0.281***	-0.279 ***
	(0.281)	(0.047)	(0.048)	(0.045)
θ_2		0.890***	0.893***	0.893 ***
		(0.068)	(0.069)	(0.068)
θ_3				
mxreg1	-1.207	-0.456	0.568	0.098
	(1.640)	(1.203)	(0.457)	(0.076)
Conditional volatility equation				
ω	0.156 **	0.103	0.105 **	0.105
	(0.069)	(0.085)	(0.050)	(0.082)
α_1	0.115 ***	0.114 ***	0.118 ***	0.117 ***
	(0.034)	(0.026)	(0.027)	(0.030)
β_1	0.827 ***	0.849 ***	0.845 ***	0.846 ***
	(0.046)	(0.082)	(0.036)	(0.038)
vxreg1	0.000	0.000	0.000	0.000
	(1.133)	(3.692)	(1.011)	(0.022)
AIC	3.7520	3.7440	3.7412	3.7409
BIC	3.8172	3.8254	3.8226	3.8223
HQC	3.7775	3.7759	3.7731	3.7728
LogLikelihood	-973.1473	-969.0467	-968.3208	-968.2439

Table A- 1: Estimation results for ARMA-GARCH models for Brazil IBrX Index

*Notes: the table presents results of the period 01.01.20 – 31.12.21. The dependent variable id the Brazilian stock market index IBrX. The independent variables are growth rate of the cumulated new reported COVID cases (GR cum.CC), the growth rate of cumulated new mortality cases (GR cum.MC), growth rate of economic policy uncertainty index (GR EPU) and the natural logarithm of government response index (LN GRI). The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations.*

Parameters	GR cum.CC	GR cum.MC	GR EPU	LN GRI
Conditional mean equation				
$\boldsymbol{\mu}$	0.086*	0.083*	0.084*	-0.044
	(0.045)	(0.046)	(0.044)	(0.208)
$\boldsymbol{\varphi_1}$	-1.252	-0.6065	0.886***	0.985***
	(1.218)	(0.547)	(0.023)	(0.008)
$\boldsymbol{\varphi_2}$	-0.550		-0.021	0.007
	(0.958)		(0.042)	(0.025)
$\boldsymbol{\varphi_3}$			-0.603***	-0.600***
			(0.030)	(0.015)
$\boldsymbol{\theta_1}$	1.233	0.578	-0.928***	-1.039***
	(1.210)	(0.562)	(0.001)	(0.000)
$\boldsymbol{\theta_2}$	0.549		0.069***	0.059***
	(0.943)		(0.002)	(0.001)
$\boldsymbol{\theta_3}$			0.608***	0.587***
			(0.001)	(0.003)
mxreg1	-1.070	0.129	0.747	0.033
	(0.928)	(1.056)	(0.456)	(0.054)
Conditional volatility equation				
$\boldsymbol{\omega}$	0.133***	0.050	0.048**	0.045
	(0.050)	(0.037)	(0.021)	(0.037)
$\boldsymbol{\alpha_1}$	0.086**	0.107***	0.112***	0.102***
	(0.027)	(0.036)	(0.026)	(0.023)
$\boldsymbol{\beta_1}$	0.760***	0.863***	0.858***	0.870***
	(0.065)	(0.068)	(0.029)	(0.029)
vxreg1	3.641**	0.000	0.000	0.000
	(1.598)	(1.231)	(0.547)	(0.010)
AIC	3.0687	3.0970	3.0874	3.0877
BIC	3.1501	3.1622	3.1852	3.1854
HQC	3.1006	3.1226	3.1257	3.1260
LogLikelihood	-792.4644	-801.8783	-795.3653	-795.4337

Table A- 2: Estimation results for ARMA-GARCH models for Russian MOEX Index

*Notes: the table presents results of the period 01.01.20 – 31.12.21. The dependent variable id the Russian stock market index IMOEX. The independent variables are growth rate of the cumulated new reported COVID cases (GR cum.CC), the growth rate of cumulated new mortality cases (GR cum.MC), growth rate of economic policy uncertainty index (GR EPU) and the natural logarithm of government response index (LN GRI). The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations.*

Parameters	GR cum.CC	GR cum.MC	GR EPU	LN GRI
Conditional mean equation				
μ	-0.075 ***	0.121 ***	0.136 ***	-0.007
	(0.000)	(0.000)	(0.190)	(0.170)
φ_1	0.326 ***	-0.910 ***	0.006 ***	-0.920 ***
	(0.000)	(0.000)	(0.002)	(0.009)
φ_2	0.665 ***	0.881 ***	0.932 ***	0.860 ***
	(0.001)	(0.001)	(0.000)	(0.013)
φ_3		0.973 ***		0.959 ***
		(0.001)		(0.011)
θ_1	-0.312 ***	0.889 ***	0.045 ***	0.916 ***
	(0.000)	(0.000)	(0.000)	(0.006)
θ_2	-0.729 ***	-0.950 ***	-1.001 ***	-0.898 ***
	(0.000)	(0.000)	(0.000)	(0.006)
θ_3	0.015 ***	-1.003 ***	-0.017 ***	-0.975 ***
	(0.000)	(0.000)	(0.000)	(0.002)
mxreg1	-0.308 ***	-3.934 ***	-0.758 ***	0.033
	(0.000)	(0.001)	(0.002)	(0.042)
Conditional volatility equation				
ω	0.099 ***	0.054 **	0.035 **	0.037
	(0.035)	(0.024)	(0.015)	(0.053)
α_1	0.098 **	0.128 ***	0.117 ***	0.115 ***
	(0.038)	(0.031)	(0.024)	(0.025)
β_1	0.774 ***	0.830 ***	0.864 ***	0.866 ***
	(0.000)	(0.048)	(0.025)	(0.026)
vxreg1	2.909 ***	0.535	0.394	0.000
	(0.237)	(0.999)	(0.395)	(0.014)
AIC	3.0229	3.0107	3.0309	3.0390
BIC	3.1125	3.1085	3.1205	3.1368
HQC	3.0580	3.0490	3.0660	3.0773
LogLikelihood	-779.4798	-775.3085	-781.5858	-782.708

Table A- 3: Estimation results for ARMA-GARCH models for Indian NIFTY 500 Index

*Notes: the table presents results of the period 01.01.20 – 31.12.21. The dependent variable id the Russian stock market index NIFTY 500. The independent variables are growth rate of the cumulated new reported COVID cases (GR cum.CC), the growth rate of cumulated new mortality cases (GR cum.MC), growth rate of economic policy uncertainty index (GR EPU) and the natural logarithm of government response index (LN GRI). The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations.*

Parameters	GR cum.CC	GR cum.MC	GR EPU	LN GRI
Conditional mean equation				
μ	0.057 **	0.061 **	0.054 **	0.841 ***
	(0.024)	(0.028)	(0.026)	(0.000)
φ_1	0.010	-0.005	0.019	0.063 ***
	(0.044)	(0.072)	(0.023)	(0.000)
φ_2	0.887 ***	0.886 ***	0.886 ***	0.905 ***
	(0.008)	(0.072)	(0.021)	(0.002)
φ_3	0.000	0.010		
	(0.997)	(0.047)		
θ_1	-0.009	-0.006	-0.015 ***	-0.055 ***
	(0.134)	(0.049)	(0.001)	(0.000)
θ_2	-0.945 ***	-0.944 ***	-0.942 ***	-0.976 ***
	(0.016)	(0.050)	(0.004)	(0.000)
θ_3				
mxreg1	0.105	-0.134	0.980	-0.199 ***
	(0.208)	(0.585)	(0.948)	(0.000)
Conditional volatility equation				
ω	0.051 **	0.059 **	0.057	0.064
	(0.024)	(0.027)	(0.041)	(0.127)
α_1	0.066 ***	0.070 ***	0.063 ***	0.075 ***
	(0.019)	(0.020)	(0.021)	(0.018)
β_1	0.901 ***	0.891 ***	(0.908) ***	0.892 ***
	(0.024)	(0.027)	(0.033)	(0.026)
vxreg1	0.530 **	1.068 **	0.000	0.000
	(0.038)	(0.475)	(1.041)	(0.034)
AIC	3.4534	3.4426	3.4948	3.4776
BIC	3.5430	3.5322	3.5762	3.5590
HQC	3.4885	3.4777	3.5267	3.5095
LogLikelihood	-892.0712	-889.2472	-903.8808	-899.3851

Table A- 4: Estimation results for ARMA-GARCH models for Chinese Shenzhen Component Index

*Notes: the table presents results of the period 01.01.20 – 31.12.21. The dependent variable id the Chinese stock market index SZI. The independent variables are growth rate of the cumulated new reported COVID cases (GR cum.CC), the growth rate of cumulated new mortality cases (GR cum.MC), growth rate of economic policy uncertainty index (GR EPU) and the natural logarithm of government response index (LN GRI). The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations.*

Parameters	GR cum.CC	GR cum.MC	GR EPU	LN GRI
Conditional mean equation				
μ	0.054 *** (0.000)	0.078 (0.048)	0.073 (0.049)	-0.075 *** (0.001)
φ_1	0.024 ** (0.009)	1.580 *** (0.009)	-0.873 *** (0.105)	-1.723 *** (0.001)
φ_2	0.960 *** (0.014)	-.0973 *** (0.011)		-0.723 *** (0.000)
φ_3	-0.012 ** (0.006)			
θ_1	-0.040 *** (0.000)	-1.600 *** (0.000)	0.906 *** (0.089)	1.781 *** (0.000)
θ_2	-0.995 *** (0.000)	1.010 *** (0.000)		0.761 *** (0.000)
θ_3				-0.018) *** (0.000)
mxreg1	-2.629 *** (0.000)	0.276 (0.209)	-1.013 (1.995)	0.040 *** (0.012)
Conditional volatility equation				
ω	0.236 *** (0.074)	0.134 *** (0.046)	0.135 *** (0.045)	0.111 *** (0.036)
α_1	0.120 *** (0.040)	0.157 *** (0,047)	0.163 *** (0.054)	0.135 *** (0.010)
β_1	0.652 *** (0.094)	0,754 *** (0.068)	0.760 *** (0.065)	0.793 *** (0.020)
vxreg1	5.407 ** (2.373)	0.407 (0.996)	0.000 (3.048)	0.000 (0.009)
AIC	3.1644	3.1904	3.2355	3.2118
BIC	3.2539	3.2719	3.3029	3.3014
HQC	3.1994	3.2223	3.2620	3.2469
LogLikelihood	-816.48	-824.2962	-800.875	-828.8852

Table A- 5: Estimation results for ARMA-GARCH models for South African FTSE/JSE Africa all share Index

*Notes: the table presents results of the period 01.01.20 – 31.12.21. The dependent variable id the South African stock market index FTSE/JSE Africa all share. The independent variables are growth rate of the cumulated new reported COVID cases (GR cum.CC), the growth rate of cumulated new mortality cases (GR cum.MC), growth rate of economic policy uncertainty index (GR EPU) and the natural logarithm of government response index (LN GRI). The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations.*

	GR cum.CC		GR cum.MC		GR EPU		LN GRI	
Weighted Ljung-Box Test on Standardized Residuals								
	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value
Lag [1]	0.001	0.972	0.787	0.375	0.725	0.395	0.988	0.320
Lag [5]	0.352	1.000	4.896	0.973	4.900	0.972	4.963	0.964
Lag [9]	3.234	0.852	8.024	0.791	8.052	0.787	7.900	0.808
Weighted Ljung-Box Test on Standardized Squared Residuals								
Lag [1]	0.002	0.967	0.151	0.697	0.136	0.713	0.173	0.677
Lag [5]	1.390	0.767	1.077	0.842	0.946	0.872	1.127	0.830
Lag [9]	6.661	0.229	4.825	0.456	4.553	0.498	4.535	0.501
Weighted ARCH LM Tests								
ARCH Lag [3]	2.195	0.139	0.926	0.336	0.697	0.404	1.097	0.245
ARCH Lag [5]	2.313	0.406	1.522	0.587	1.288	0.650	1.442	0.608
ARCH Lag [7]	2.346	0.644	1.695	0.781	1.458	0.830	1.586	0.804

Table A- 6: Results of the adequacy check of models for Brazil IBrX Index

*Notes: the table provides the empirical statistics of Ljung-Box for the autocorrelation in standardized errors and both Ljung-Box and ARCH LM tests, which denote to test for homoscedasticity. The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations.*

	GR cum.CC		GR cum.MC		GR EPU		LN GRI	
Weighted Ljung-Box Test on Standardized Residuals								
	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value
Lag [1]	0.012	0.913	0.249	0.618	0.331	0.565	0.265	0.606
Lag [5]	2.677	1.000	1.220	1.000	3.985	1.000	3.771	1.000
Lag [9]	4.510	0.998	2.424	0.958	8.583	0.9951	8.982	0.992
Weighted Ljung-Box Test on Standardized Squared Residuals								
Lag [1]	2.286	0.1305	2.326	0.127	1.052	0.305	2.149	0.143
Lag [5]	5.107	0.145	9.085	0.016	8.647	0.020	8.554	0.021
Lag [9]	6.091	0.288	10.863	0.033	10.695	0.035	10.538	0.038
Weighted ARCH LM Tests								
ARCH Lag [3]	0.010	0.919	0.072	0.788	0.448	0.504	0.049	0.825
ARCH Lag [5]	1.147	0.690	0.149	0.977	0.582	0.859	0.143	0.978
ARCH Lag [7]	1.460	0.829	1.181	0.883	1.867	0.746	1.353	0.850

Table A- 7: Results of the adequacy check of models for Russian MOEX Index

*Notes: the table provides the empirical statistics of Ljung-Box for the autocorrelation in standardized errors and both Ljung-Box and ARCH LM tests, which denote to test for homoscedasticity. The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations.*

	GR cum.CC		GR cum.MC		GR EPU		LN GRI	
Weighted Ljung-Box Test on Standardized Residuals								
	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value
Lag [1]	0.096	0.756	3.467*	0.063	0.929	0.335	3.912*	0.048
Lag [5]	8.798**	0.019	9.893*	0.070	6.269	0.985	9.201	0.360
Lag [9]	14.794	0.187	15.045	0.468	12.458	0.478	14.161	0.591
Weighted Ljung-Box Test on Standardized Squared Residuals								
Lag [1]	0.515	0.473	1.335	0.248	1.215	0.270	1.662	0.197
Lag [5]	0.710	0.921	1.846	0.655	2.594	0.486	3.390	0.340
Lag [9]	1.785	0.929	2.863	0.781	4.606	0.490	5.599	0.347
Weighted ARCH LM Tests								
ARCH Lag [3]	0.248	0.619	0.028	0.867	1.379	0.240	1.704	0.192
ARCH Lag [5]	0.347	0.928	1.115	0.699	2.425	0.385	2.998	0.290
ARCH Lag [7]	1.304	0.860	1.329	0.855	3.312	0.457	3.458	0.432

Table A- 8: Results of the adequacy check of models for Indian NIFTY 500 Index

*Notes: the table provides the empirical statistics of Ljung-Box for the autocorrelation in standardized errors and both Ljung-Box and ARCH LM tests, which denote to test for homoscedasticity. The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations.*

	GR cum.CC		GR cum.MC		GR EPU		LN GRI	
Weighted Ljung-Box Test on Standardized Residuals								
	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value
Lag [1]	0.317	0.574	0.618	0.432	0.003	0.956	0.417	0.518
Lag [5]	2.703	1.000	3.311	1.000	2.346	1.000	3.492	1.000
Lag [9]	5.095	1.000	5.815	1.000	3.498	1.000	4.816	0.996
Weighted Ljung-Box Test on Standardized Squared Residuals								
Lag [1]	0.071	0.789	0.124	0.725	0.065	0.798	0.201	0.654
Lag [5]	0.854	0.892	1.005	0.859	0.427	0.968	0.755	0.912
Lag [9]	2.130	0.889	2.424	0849	2.115	0.891	3.069	0.748
Weighted ARCH LM Tests								
ARCH Lag [3]	0.063	0.801	0.020	0.888	0.000	0.995	0.015	0.904
ARCH Lag [5]	0.953	0.747	1.006	0.731	0.715	0.819	0.966	0.743
ARCH Lag [7]	1.796	0.760	1.932	0.732	2.558	0.601	3.500	0.424

Table A- 9: Results of the adequacy check of models for Chinese Shenzhen Component Index

*Notes: the table provides the empirical statistics of Ljung-Box for the autocorrelation in standardized errors and both Ljung-Box and ARCH LM tests, which denote to test for homoscedasticity. The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations.*

	GR cum.CC		GR cum.MC		GR EPU		LN GRI	
Weighted Ljung-Box Test on Standardized Residuals								
	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value
Lag [1]	0.030	0.862	0.111	0.738	0.017	0.897	0.129	0.719
Lag [5]	3.499	1.000	1.647	1.000	0.604	1.000	3.233	1.000
Lag [9]	8.076	0.968	4.620	0.997	1.428	0.998	7.977	0.971
Weighted Ljung-Box Test on Standardized Squared Residuals								
Lag [1]	0.022	0.881	0.968	0.325	1.024	0.312	0.814	0.367
Lag [5]	3.062	0.396	4.965	0.156	4.185	0.232	3.904	0.266
Lag [9]	6.904	0.207	7.214	0.182	5.857	0.315	5.890	0.311
Weighted ARCH LM Tests								
ARCH Lag [3]	0.027	0.870	4.690	0.030	3.616*	0.057	3.272*	0.070
ARCH Lag [5]	6.239*	0.053	7.206	0.031	5.651*	0.073	5.527*	0.078
ARCH Lag [7]	8.471**	0.041	7.882	0.056	6.068	0.137	6.344	0.120

Table A- 10: Results of the adequacy check of models for South African FTSE/JSE Africa all share Index

*Notes: the table provides the empirical statistics of Ljung-Box for the autocorrelation in standardized errors and both Ljung-Box and ARCH LM tests, which denote to test for homoscedasticity. The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations.*

Parameters	Communic. Services	Consumer Discretion.	Consumer Staples	Energy	Financials	Health Care	Industrials	Inform. Technology	Materials	Real Estate
Conditional mean equation										
$\boldsymbol{\mu}$	0.186**	0.083***	-0.013	0.158***	0.106***	0.152**	0.160***	-0.082	0.066***	0.042
	(0.74)	(0.000)	(0.061)	(0.000)	(0.000)	(0.070)	(0.018)	(0.066)	(0.000)	(0.065)
$\boldsymbol{\varphi_1}$	1.808***	-0.511***	-1.762***	0.968***	1.648***	-1.475***	-1.495***	0.485***	0.113***	0.417
	(0.002)	(0.000)	(0.002)	(0.008)	(0.000)	(0.355)	(0.000)	(0.124)	(0.000)	(0.308)
$\boldsymbol{\varphi_2}$	-0.967***	0.412***	-0.975***		-1.535***	-0.696***	-0.838***		0.852***	
	(0.004)	(0.000)	(0.003)		(0.000)	(0.256)	(0.000)		(0.000)	
$\boldsymbol{\varphi_3}$		0.924***			0.845***		0.108***		-0.019***	
		(0.001)			(0.000)		(0.000)		(0.002)	
$\boldsymbol{\theta_1}$	-1.841***	0.458***	1.773***	-0.955***	-1.576***	1.461***	1.608***	-0.631***	-0.135***	-0.313
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.385)	(0.000)	(0.091)	(0.000)	(0.322)
$\boldsymbol{\theta_2}$	0.998***	-0.502***	0.998***	-0.967***	1.324***	0.646**	1.015***		-0.895***	
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.299)	(0.000)		(0.000)	
$\boldsymbol{\theta_3}$		-1.012***		0.034***	-0.768***					
		(0.001)		(0.000)	(0.000)					
mxreg1	-3.104**	0.837***	-0.752	-3.299***	-2.896***	-0.362	-2.058***	1.381	-1.359***	-1.696
	(1.450)	(0.000)	(0.475)	(0.001)	(0.001)	(1.373)	(0.519)	(2.214)	(0.001)	(1.597)
Conditional volatility equation										
$\boldsymbol{\omega}$	0.228**	0.552***	0.456***	1.643*	0.095**	0.463**	0.290***	2.521***	1.143***	0.107**
	(0.116)	(0.190)	(0.151)	(0.863)	(0.047)	(0.207)	(0.105)	(0.531)	(0.000)	(0.044)
$\boldsymbol{\alpha_1}$	0.077**	0.120***	0.131***	0.024**	0.230***	0.119***	0.200***	0.868***	0.117	0.167***
	(0.032)	(0.036)	(0.151)	(0.010)	(0.076)	(0.046)	(0.058)	(0.196)	(0.089)	(0.043)
$\boldsymbol{\beta_1}$	0.831***	0.666***	0.588***	0.651***	0.756***	0.683***	0.636***	0.025	0.474***	0.771***
	(0.066)	(0.081)	(0.106)	(0.180)	(0.060)	(0.111)	(0.087)	(0.045)	(0.161)	(0.048)
vxreg1	6.697**	3.936**	10.485**	15.619*	2.208*	5.121*	8.003**	70.767***	28.817**	4.926**
	(2.823)	(1.862)	(4.229)	(9.030)	(1.331)	(2.778)	(3.653)	(21.494)	(13.253)	(2.208)
AIC	4.142	3.937	3.633	4.681	3.633	3.879	3.701	4.788	4.171	3.639
BIC	4.224	4.034	3.714	4.763	3.731	3.960	3.791	4.853	4.261	3.704
HQC	4.174	3.975	3.665	4.713	3.672	3.911	3.736	4.812	4.207	3.665
LogLikelihood	-1072.205	-1017.422	-939.921	-1214.129	-938.129	-1004.264	-956.853	-1243.963	-1079.85	-943.604

Table A- 11: Estimation results of ARMA-GARCH models with GR cum.CC as exogenous variable

Notes: The dependent variable are sectors indices. The independent variable is growth rate of the cumulated new reported COVID cases (GR cum.CC).

*The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations*

Parameters	Communic. Services	Consumer Discretion.	Consumer Staples	Energy	Financials	Health Care	Industrials	Inform. Technology	Materials	Real Estate
Conditional mean equation										
μ	-0.111	0.192***	-0.131	-0.270	-0.180**	-0.153***	-0.457***	-0.105***	-0.079***	-0.292
	(0.307)	(0.000)	(0.155)	(0.384)	(0.074)	(0.000)	(0.000)	(0.000)	(0.012)	(0.186)
φ_1	1.810***	0.941***	-1.861***	-0.749***	1.035***	-0.381***	-0.605***	0.909***	-1.992***	0.439
	(0.012)	(0.014)	(0.003)	(0.256)	(0.049)	(0.000)	(0.000)	(0.012)	(0.001)	(0.276)
φ_2	-0.969***		-0.985***		-0.115**	0.682***	0.973***		-1.003***	
	(0.013)		(0.006)		(0.049)	(0.000)	(0.000)		(0.000)	
φ_3						0.643***	0.603***		-0.008***	
						(0.000)	(0.000)		(0.000)	
θ_1	-1.841***	-0.998***	1.867***	0.788***	-0.981***	0.275***	0.621***	-1.084***	2.015***	-0.324
	(0.004)	(0.000)	(0.002)	(0.236)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.289)
θ_2	0.999***	-0.020***	0.999***			-0.776***	-1.034***	0.065***	1.016***	
	(0.001)	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)	(0.000)	
θ_3						-0.559***	-0.647***			
						(0.000)	(0.000)			
mxreg1	0.070	-0.029***	0.032	0.111	0.068***	0.060***	0.127***	0.085***	0.053***	0.089*
	(0.079)	(0.000)	(0.040)	(0.097)	(0.020)	(0.000)	(0.000)	(0.000)	(0.020)	(0.048)
Conditional volatility equation										
ω	0.189*	0.461**	0.096	0.514*	0.120*	0.246*	0.145	0.138	0.235**	0.064
	(0.108)	(0.000)	(0.060)	(0.266)	(0.068)	(0.149)	(0.094)	(0.104)	(0.108)	(0.040)
α_1	0.131***	0.136***	0.203***	0.062	0.225***	0.190***	0.174***	0.786***	0.122***	0.193***
	(0.033)	(0.040)	(0.060)	(0.050)	(0.049)	(0.063)	(0.051)	(0.124)	(0.017)	(0.040)
β_1	0.820***	0.719***	0.752***	0.863***	0752***	0.654***	0.777***	0.241***	0.826***	0.809***
	(0.045)	(0.075)	(0.065)	(0.123)	(0.048)	(0.131)	(0.060)	(0.071)	(0.011)	(0.034)
vxreg1	0.006	0.000	0.020	0.000	0.000	0.061	0.000	0.375***	0.000	0.000
	(0.027)	(0.041)	(0.022)	(0.109)	(0.018)	(0.053)	(0.022)	(0.091)	(0.025)	(0.011)
AIC	4.178	3.953	3.656	4.740	3.661	3.870	3.709	4.564	4.207	3.674
BIC	4.260	4.057	3.738	4.805	3.734	3.968	3.807	4.637	4.297	3.739
HQC	4.210	3.982	3.688	4.766	3.690	3.909	3.747	4.562	4.242	3.700
LogLikelihood	-1082.57	-1024.833	-946.105	-1231.572	-948.369	-1000.113	-957.885	-1184.363	-1089.239	-952.779

Table A- 12: Estimation results of ARMA-GARCH models with LN GRI as exogenous variable

Notes: The dependent variable are sectors indices. The independent variable is natural logarithm of government response index (LN GRI).

*The numbers in the parentheses are the robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Source: own calculations*